PromptCharm: Text-to-Image Generation through Multi-modal Prompting and Refinement

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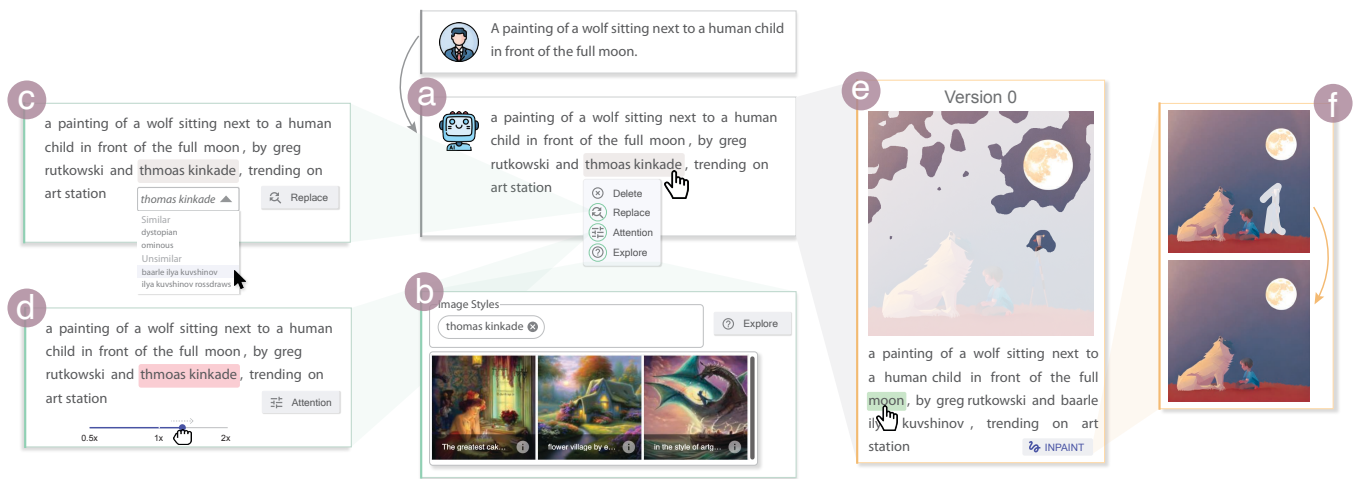
Figure 1: PromptCharm facilitates prompt engineering in text-to-image generation with an enriched, multi-modal feedback loop. (a) Given an initial prompt from a user, PromptCharm first suggests an initial refinement based on a prompt optimization model. (b) The user can explore different styles by searching them in a large database. (c) The user can also explore similar and dissimilar image styles in a drop-down list. (d) Furthermore, the user can adjust the attention of the diffusion model to different keywords in the prompt. (e) Given an initial image generated by the model, the user can examine which part of the image corresponds to which part of the text prompt. (f) The user can further mark undesired parts of an image to remove or regenerate them through an image inpainting model.

ABSTRACT

The recent advancements in Generative AI have significantly advanced the field of text-to-image generation. The state-of-the-art text-to-image model, *Stable Diffusion*, is now capable of synthesizing high-quality images with a strong sense of aesthetics. Crafting text prompts that align with the model's interpretation and the user's intent thus becomes crucial. However, prompting remains challenging for novice users due to the complexity of the stable diffusion model and the non-trivial efforts required for iteratively editing and refining the text prompts. To address these challenges, we propose PromptCharm, a mixed-initiative system that facilitates text-to-image creation through multi-modal prompt engineering and refinement. To assist novice users in prompting, PromptCharm first automatically refines and optimizes the user's initial prompt. Furthermore, PromptCharm supports the user in exploring and selecting different image styles within a large database. To assist users in effectively refining their prompts and images, PromptCharm renders model explanations by visualizing the model's attention values. If the user notices any unsatisfactory areas in the generated images, they can further refine the images through model attention adjustment or image inpainting within

the rich feedback loop of PromptCharm. To evaluate the effectiveness and usability of PromptCharm, we conducted a controlled user study with 12 participants and an exploratory user study with another 12 participants. These two studies show that participants using PromptCharm were able to create images with higher quality and better aligned with the user's expectations compared with using two variants of PromptCharm that lacked interaction or visualization support.

CCS CONCEPTS

• **Human-centered computing → Interactive systems and tools**; • **Computing methodologies → Machine learning**.

KEYWORDS

Generative AI, Prompt Engineering, Large Language Models

ACM Reference Format:
Zhijie Wang, Yuheng Huang, Da Song, Lei Ma, and Tianyi Zhang. 2024. PromptCharm: Text-to-Image Generation through Multi-modal Prompting and Refinement. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24), May 11–16, 2024, Honolulu, HI, USA.* ACM, New York, NY, USA, 21 pages. https://doi.org/10.1145/3613904.3642803

1 INTRODUCTION

The recent advancements in Generative AI have brought significant progress to text-to-image generation—an intersection field of computer vision (CV) and natural language processing (NLP). State-of-the-art (SOTA) text-to-image models such as *Stable Diffusion* [53] and *DALL-E* [50] have showcased impressive capabilities in producing images with exceptional quality and fidelity. As a result, these text-to-image models find utility across diverse domains, including visual art creation [31], news illustration [37], and industrial design [38]. According to the recent studies [36, 45], the quality of AI-generated images is highly sensitive to the text prompts. Thus, crafting text prompts (also known as *prompting* or *prompt engineering*) has emerged as a crucial step in text-to-image generation.

Previous studies have highlighted that novice users often struggle with writing prompts [31, 77]. Specifically, novice users often experience a steep learning curve when attempting to write text prompts that the model can effectively interpret while preserving their creative intentions. Moreover, generating images with a profound sense of aesthetics requires domain knowledge in creative design, particularly in employing specific modifiers (i.e., *magic words* about image styles) [36, 69]. Unfortunately, novice users often do not have such expertise.

Recently, several interactive approaches have been proposed to support prompt engineering for natural language processing [58] or computer vision tasks [5, 18, 65]. These approaches aim to guide the iterative prompt refinement process by rendering a set of alternative prompts [58] or suggesting a few new keywords for users to choose from [5, 18]. Nevertheless, existing approaches usually lack rich feedback during the user's creation process. For instance, users may wonder to what extent the model has incorporated their text prompts during the generation. However, without appropriate support to explain the model's generation, the user may find it difficult to interpret a generated image. As a result, they do not

know which part of their prompts has worked and which has not. Thus, they may feel clueless when refining their text prompts for the new iteration.

The deficiency of lacking proper feedback becomes especially pronounced when confronted with the situation that the model's output does not align with a user's intention. For instance, a subject mentioned in the text prompt is missing in the generated image. As a result, it becomes arduous for the user to revise their prompt effectively. This is particularly due to the complexity of the stable diffusion model and the absence of suitable model explanations. Moreover, recent studies from the ML community have shown that SOTA generative AI and large language models could actually misinterpret the user's intention in the input text prompt [20, 32]. A more tangible way to align the user's creative intentions with the model's generation becomes another urgent need in facilitating text-to-image creation.

In this paper, we present PromptCharm, a mixed-initiative system that supports the iterative refinement of AI-generated images by enabling multi-modal prompt engineering within a rich feedback loop. Since novice users might have little experience in prompting, PromptCharm leverages a SOTA prompt optimization model, *Promptist* [24], to automatically revise and improve their initial input prompts. The user can then efficiently explore different image styles and pick modifiers they are interested in through PromptCharm. The user can further examine which part of the generated image corresponds to which part of the text prompt by observing the model attention visualization in PromptCharm. As the user notices a misalignment between the generated image and their input prompts, they can refine the generated image in PromptCharm by adjusting the attention of the model to specific keywords in the given prompts. They can also mark undesired parts of an image to remove or regenerate them through an image inpainting model. With the help of PromptCharm, the user can avoid re-writing their prompts to match the model's interpretation with their creative intent, as such revision may lead to a tedious process of *trail-and-error*. Finally, PromptCharm provides version control to help users easily track their image creations within an iterative process of prompting and refinement.

To evaluate the effectiveness and usability of PromptCharm, we conducted two within-subjects user studies with a total of 24 participants who had no more than one year of experience in using text-to-image generative models. We created two variants of PromptCharm as comparison baselines (denoted as *Baseline* and *Promptist*) by disabling novel interactions and features in PromptCharm. In the first study with 12 participants featuring close-ended tasks, participants using PromptCharm were able to create images with the highest similarity to the target images across all three tasks (average SSIM: 0.648 ± 0.100) compared with the participants using Baseline (average SSIM: 0.479 ± 0.115) or Promptist (average SSIM: 0.574 ± 0.111). In the second study with another 12 participants featuring open-ended tasks, participants self-reported more satisfied with their images when using PromptCharm in terms of aesthetically pleasing compared with using Baseline (5.8 vs. 4.9, Wilcoxon signed-rank test: $p = 0.02$) and Promptist (5.8 vs. 4.9, Wilcoxon signed-rank test: $p = 0.01$) on a 7-point Likert scale. Participants also felt their images matched their expectations better

compared with using either Baseline (5.9 vs. 4.4, Wilcoxon signed-rank test: $p = 0.02$) or Promptist (5.9 vs. 4.8, Wilcoxon signed-rank test: $p = 0.04$). These results demonstrate that PromptCharm can assist users in effectively creating images with higher quality and senses of aesthetics while not requiring rich relevant experience.

In summary, this paper makes the following contributions:

- PromptCharm, a mixed-initiative interaction system that supports text-to-image creation through multi-modal prompting and image refinement for novice users. We have open-sourced our system on Github [1].
- A set of visualizations, interaction designs, and implementations for interactive prompt engineering.
- Two within-subjects user studies to demonstrate that PromptCharm facilitates users to create better and more aesthetically pleasing images compared with two baseline tools.

2 RELATED WORK

2.1 Text-to-Image Generation

Text-to-image generation stands as a pivotal capability within the realm of generative AI. Given a text input, an AI model aims to generate an image whose content is aligned with the text description. One of the pioneering attempts in the field of text-to-image generation is AlignDraw [41]. AlignDraw is extended from Draw [22], an RNN-based image generation model, by leveraging a bidirectional attention RNN language model to guide the image generation process. With the advancements in generative adversarial networks (GANs) [21], a large body of research on text-to-image generation has been focusing on GAN-based approaches [15, 33, 51, 78]. Reed et al. proposed one of the earliest GAN-based text-to-image generation models by combining GAN with a convolutional-recurrent text encoder [51]. To improve the resolution and quality of the generated images, Zhang et al. then utilized a two-stage model architecture, StackGAN, to gradually synthesize and refine an image [78]. The emergence of the transformer [60] models further enhanced the GAN model's capability of generating high-quality images [15].

Notably, the success of the transformer models in a wide range of NLP tasks has also inspired computer vision researchers. The transformer-based architecture later showed promising performance on text-to-image generation [13, 50, 71]. In 2021, Open AI released DALL-E, a GPT-3-based model for text-to-image generation [50]. Microsoft proposed NUWA, a pre-trained 3D encoder-decoder transformer for various visual synthesis tasks, including text-to-image generation [71]. Recently, denoising diffusion probabilistic models (DDPM, usually also referred as diffusion models) have surged as the dominant approach in text-to-image generation research [23, 49, 53]. Compared with GAN-based and transformer-based methods, diffusion models are capable of generating images with much higher resolutions. CLIP (contrast language-image pre-training) further enhances the diffusion model's ability to understand both linguistic and visual concepts [48]. As a result, SOTA text-to-image generation models (e.g., Stable Diffusion [53] and DALL-E2[49]) are mostly based on a pipeline of combining diffusion models with CLIP. The Stable Diffusion model [53] was

trained on the LAION dataset [54] with latent diffusion models and cross-attention layers. PromptCharm leverages the Stable Diffusion model [53] as the text-to-image generation pipeline since it is open-sourced and has SOTA performance on public benchmarks.

2.2 Prompt Engineering

The widespread use of generative models has raised the significance of prompting. As a result, an increasing number of techniques have been proposed for prompt engineering. For instance, few-shot prompting [6, 19, 79] and chain-of-thought prompting [68, 72, 74] are both representative prompting techniques for generative language models. In addition to prompting techniques, there has also been a few studies about prompting guidelines [35, 36, 45, 77]. To identify the prompts that can effectively help text-to-image models generate coherent outputs, Liu et al. conducted user studies with practitioners to derive a set of prompt design guidelines [36]. They specifically found that style keywords (modifiers) play a vital role in affecting the generated image's quality. This is also confirmed by a recent study on the taxonomy of prompt modifiers for text-to-image generation [45].

Since hand-crafting prompts require significant manual efforts, another line of research has focused on automated prompt generation [24, 46, 55, 65, 70]. Specifically, for text-to-image generation, recent research efforts have been focusing on automatically optimizing user input prompts and extending them with effective image style keywords (modifiers) [24, 46, 70]. For instance, Wen et al. proposed a method to learn prompts that can be re-used across different image generation models through gradient-based discrete optimization. Notably, our work complements this line of research, since PromptCharm can be combined with any automated prompting methods for text-to-image generative models. We specifically select Promptist [24], a reinforcement learning-based method, as our prompt refinement model given its superior performance.

Our work is most related to the interactive prompt engineering [5, 18, 58]. Strobelt et al. proposed PromptIDE, an interactive user interface to help users explore different prompting options for NLP tasks [58]. To assist novice users in prompting for text-to-image generation, Promptify provides an interactive user interface that allows users to explore different generated images and iteratively refine their prompts based on the suggestions from a GPT3 model [5]. Another recent work, PromptMagician, utilizes an image browser to support users to efficiently explore and compare the generated images with images retrieved from a database [18]. Both Promptify and PromptMagician aim at assisting users in exploring a large set of different generated images when revising text prompts. Different from them, PromptCharm focuses on helping users iteratively improve one generated image through multi-modal prompting by adjusting the model's attention to keywords in the prompt. By adjusting the model's attention, the user does not need to rewrite their prompts to align the model's interpretation with their creative intention. Therefore, they can avoid risking completely changing the image content when revising the prompt. Another recent work, PromptPaint, also supports prompting beyond text by providing flexible steering through paint medium-like interactions [12]. By masking undesired areas and directly inpaint them, the user could efficiently remove or regenerate some areas of

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[1]https://github.com/ma-labo/PromptCharm

an image while preserving the other areas. Different from Prompt-Paint, PromptCharm further provides model explanations to help users interpret the model's generation. Subsequently, users can improve the generated images by enhancing specific parts of images or prompts identified by observing model explanations.

Note that open-sourced tools outside of academic research such as *Stable Diffusion Web UI* (SD Web UI) [1] also provides similar features such as attention adjustment and visualization. However, PromptCharm is different from SD Web UI in the following ways. First, SD Web UI only provides attention visualization over the image (such as a heatmap). By contrast, PromptCharm visualizes model attention to text prompts and the influence of each prompt token on the image. Thus, the attention visualization from PromptCharm is designed to help users refine prompt tokens based on model attention. Furthermore, PromptCharm's interface has gone through multiple rounds of careful design. For instance, users can simply hover over a token to see its influence on the image in PromptCharm. However, SD Web UI requires users to type keywords in order to visualize their heatmaps over the generated image. When adjusting model attention, users can drag a slider in PromptCharm to adjust attention. By contrast, they have to manually add a bracket behind a token and enter a decimal value to adjust the attention of this token when using SD Web UI. Finally, PromptCharm and its features' effectiveness are confirmed through two user studies with 24 participants.

2.3 Interactive Support for Generative Design

Our work is also related to generative design. Early attempts on generative design covering both 2D [10, 76] and 3D design [9, 10, 29, 42, 75], which mostly focus on assisting users in exploring a diverse set of design alternatives. For instance, Matejka et al. proposed DreamLens, an interactive system for exploring and visualizing large-scale generative design datasets [43]. The most related generative design work to us includes those using AI models to support user's design [11, 17, 31, 37, 38, 64, 73]. Evirgen et al. proposed GANzilla, a tool that allows users to discover image manipulation directions in Generative Adversarial Networks (GANs) [16]. Its follow-up work, GANravel, focuses on disentangling editing directions in GANs [17]. To achieve this, both GANzilla and GANravel adjust the coefficients in GAN's latent space. Different from them, PromptCharm supports controlling the editing effects by adjusting the model's attention to text prompt. To generate images for news illustration, Liu et al. proposed Opal, an interactive system based on GPT 3 (a large language model) and VQGAN [37]. Opal supports image style suggestion by leveraging a *Sentence-BERT* for asymmetric semantic search. By contrast, PromptCharm not only leverages a state-of-the-art reinforcement learning-based model, *Promptist* [24], to automatically refine prompts, but also provides a database for user's exploration. 3DALL-E integrates OpenAI's DALL-E (a text-to-image generative model), GPT-3 and CLIP to inspire professional CAD designers' 3D design work through 2D images' prototyping [38]. As a complementary study to the prior research, Ko et al. conducted an interview study with 28 visual artists to help the research community understand the potential and design guidelines of using large-scale text-to-image models for visual art creations [31]. Overall, our work contributes to this area

through a mixed-initiative system that helps users iteratively improve text-to-image creation through a set of multi-modal prompting supports, including automated prompt refinement, modifier exploration, model attention adjustment, and image inpainting.

2.4 Human-AI Collaboration

Prompt engineering is a typical form of human-AI collaboration, where prompting serves as the interface between human users and generative models. As a result, the design of PromptCharm is highly motivated by the recent guidelines and design principles for human-AI collaboration [3, 7, 8, 14, 34, 61]. For instance, Amershi et al. derived 18 design guidelines about human-AI interaction based on over 150 AI-related design recommendations collected from academic and industry sources. The design of PromptCharm follows two specific guidelines. First, to *make clear why the system did what it did*, PromptCharm provides model explanations of the AI-generated images through model attention visualization. Second, to *enable the user to provide feedback during interaction with the AI system*, PromptCharm enriches the feedback loop of text-to-image generation through the model attention adjustment and image inpainting. Liao et al. investigated user needs about XAI through interviewing 20 UX and design practitioners [34]. They categorized the user needs about XAI into four categories: *explain the model*, *explain a prediction*, *inspect counterfactual*, and *example based*. The design of PromptCharm carefully addresses the need of *explaining a prediction*. Specifically, PromptCharm visualizes the model's attention to different words in the prompts by using different background colors. Moreover, when users hover over a specific word, PromptCharm further highlights the corresponding parts in the generated image. Overall, the design of PromptCharm addresses two critical challenges in human-AI collaboration through its mixed-initiative interaction design: handling the imperfection of AI models and aligning the model's interpretation with the user's creative intent.

3 USER NEEDS AND DESIGN RATIONALE

3.1 User Needs in Prompt Engineering and Creative Design

To understand the needs of users, we conducted a literature review of previous work that has done a formative study or a user study about prompt engineering [5, 31, 36, 58, 65, 72, 77] [2] or generative design [11, 16, 43, 73]. We also reviewed the previous work that has discussed the challenges and design guidelines with generative AI [45, 69]. Based on this review, we summarize five major user needs for interactive prompt engineering in text-to-image generation.

N1: Automatically recommending and revising text prompts. Recent studies have shown that novices often struggle with writing prompts and wish to have some suggestions on how to revise their prompts [31, 77]. For instance, through a user study with ten non-experts, Zamfirescue-Pereira et al. found that half of the participants did not know where to start when writing text prompts to solve a given task [77]. After an interview with 28 visual artists who wish

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[2] Note that we only consider insights from prompting with LLMs that are generalizable to text-to-image generation.

to use generative AI for their own work, Ko et al. suggested that a text prompt engineering tool that can recommend or revise the prompts is an urgent need [31].

N2: Balancing automation and user's control. Users who use AI for creative design prefer to gain control to some extent instead of having full automation [11, 45, 69, 73]. Through a user study with five professionals in digital comics creation, Yan et al. emphasized the importance of automation-control balance in Human-AI co-creation [73]. Specifically, through a user study with twelve participants, Evirgen et al. found that users wish to decide how strongly editing effects to be applied to an image generated by Generative Adversarial Networks (GANs) [16]. Specifically, the user appreciates changing such strength both positively and negatively.

N3: Supporting users explore different prompting options. Different prompting options may yield completely different results from a generative AI model. Through a user-centered design process with NLP researchers, Strobelt et al. found that a prompt engineering tool should provide the user with the human-in-the-loop ability to explore and select different variations of prompts [58]. For text-to-image creation, user needs particularly lie in the selection of image modifiers that have significant impacts on the quality and style of the generated images as mentioned in the previous studies [5, 36, 45]. Through a formative study with six experienced stable diffusion users, Brade et al. highlighted the challenge of discovering effective prompting modifiers [5]. They found that users need significant effort to find keywords related to a specific image style when seeking guidance from online communities. Therefore, PromptCharm should assist users in discovering diverse image modifiers.

N4: Version control to keep track through iterations. During an iterative creating process, users may wish to compare their current contents with previous iterations at some point [5, 16, 69]. For instance, Weisz et al. found that versioning and visualizing differences between different outputs could be helpful since users may prefer earlier outputs to later ones [69]. Evirgen et al. found that keeping track of all steps could provide users more guidance once they were stuck with generative AI [16].

N5: Providing explanations for generated contents. Explanations could help users better understand the generated content and gain insights for further improvements [5, 16, 69, 77]. Zamfirescu-Pereira et al. found that users could face understanding barriers, e.g., why the model did not produce expected outputs [77]. Strobelt et al. found that a prompt engineering tool should provide the user with the human-in-the-loop ability with rich feedback to iteratively improve their prompt writing [58]. Therefore, providing proper explanations can help calibrate users' trust with generative AI's capabilities and limitations [69]. Specifically, Evirgen et al. highlighted the possibility of providing users with explanations through an informative visualization design, e.g., heat map [16].

3.2 Design Rationale

To support **N1**, PromptCharm leverages a state-of-the-art model, *Promptist* [24], to automatically revise user's input text prompt. After the user types their initial prompt and clicks on the PROMPT button, PromptCharm will improve the user's prompt through

re-organizing and appending suggested modifiers (Fig. 2 ⓐ). In order to balance automation and user's control (**N2**), PromptCharm provides multi-modal prompting within an interactive text box (Fig. 2 ⓑ). In this text box, the user can **Delete**, **Explore**, or **Replace** one or multiple image modifiers. By exploring different modifiers, the user can know how these keywords would possibly affect the generated images without actually rendering it. If the user encounters any modifiers that they dislike, they can efficiently replace them with other similar/dissimilar modifiers in PromptCharm. This design also allows the user to explore different prompting options (**N3**). Note that an alternative design choice for **N3** could be generating and displaying a large set of images for the user to explore given different suggested prompts. However, such a design might be overwhelming for novice users. For example, when leveraging text-to-image models for news illustration, Liu et al. found that returning a large amount of choices could at times be *overwhelming, repetitive, or over specifc* [37]. Moreover, during our experiments, we found that generating one image with a NVIDIA A5000 GPU (24 GB VRAM) could take around 30 seconds. Generating a large set of images would require much more computational resources or introduce a longer waiting time for users. Thus, PromptCharm focuses on helping users iteratively refine their images instead of rendering a set of images for users to select.

To guide users iteratively improving their creations, PromptCharm provides model explanations by visualizing the model's attention after each iteration (**N5**). By observing the attention values of different words in the input prompt, the user can quickly identify if the model's interpretation of the prompt was aligned with their intent, e.g., whether there is an important keyword the model does not pay attention to (Fig. 2 ⓒ). Moreover, PromptCharm assists users in interpreting the model's generation by highlighting the parts of the image that correspond to a keyword in the text prompt. If the user observes any misalignment between the model's interpretation and their creative intent, they can refine the generated image through adjusting the model's **Attention** to the keywords in the prompts (Fig. 2 ⓓ). If the generated image includes undesired parts, the user can also mask these parts and re-generate them through an image inpainting model in PromptCharm without spending more effort on rewriting prompts (Fig. 2 ⓔ). This is highly motivated by the idea of direct manipulation [56, 57]. Both the model attention adjustment and the image inpainting can also support **N2**. Finally, to support **N4**, PromptCharm provides version control to help users keep track through multiple iterations. By clicking on the labels of different versions, the user can quickly glance and compare their text prompts and synthesized images from different rounds of iterations.

4 DESIGN AND IMPLEMENTATION

In this section, we introduce the design and implementation of PromptCharm. Specifically, we first introduce PromptCharm's *multi-modal* prompting and refinement: (1) Text Prompt Refinement, Suggestion, and Exploration (Sec. 4.1). (2) Model Attention-based Explanation and Refinement (Sec. 4.2). (3) Direct Manipulation via Inpainting and Masked Image Generation (Sec. 4.3). Then we
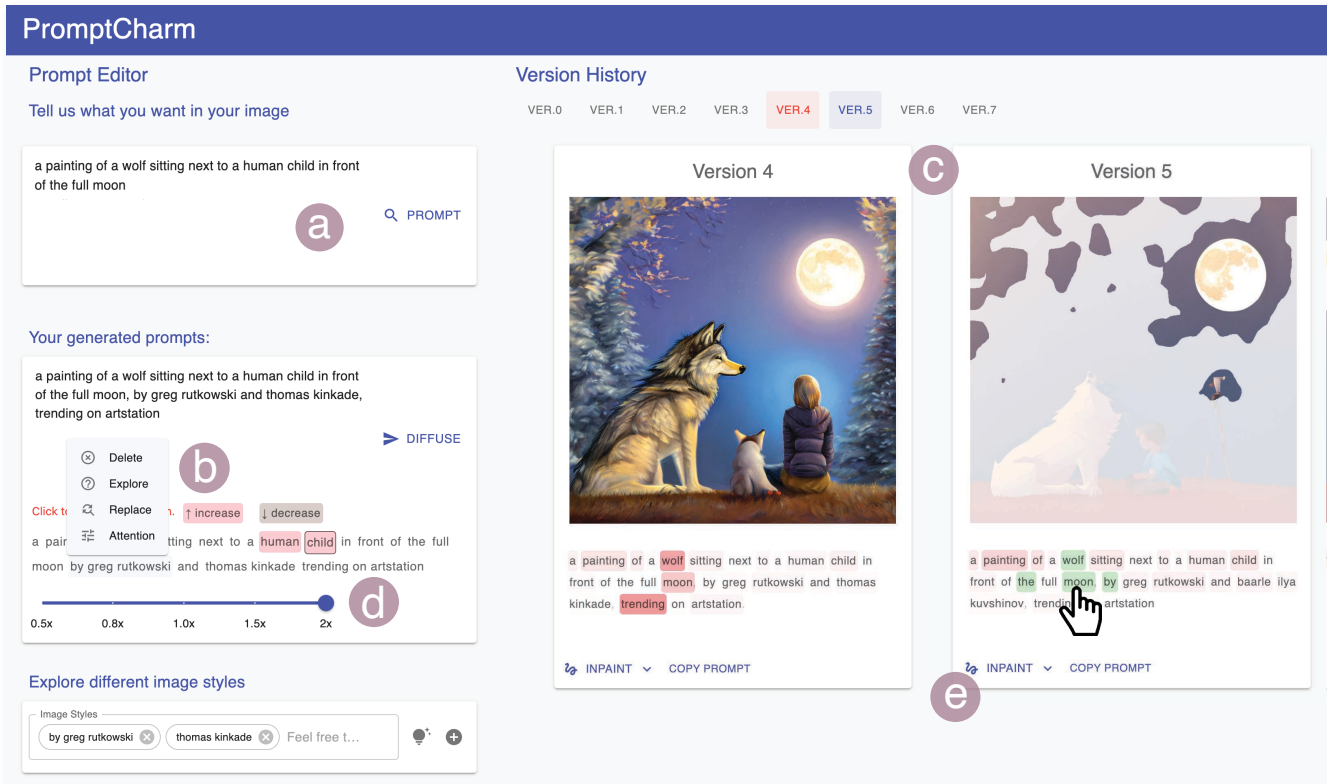
Figure 2: User interface of PromptCharm. (a) The user can first type their initial input prompt in a text box. PromptCharm will then automatically refine the user's prompt. (b) PromptCharm further supports users in efficiently exploring different image styles. (c) The user can then examine the generated images with the help of model attention visualization. If they would like to refine the image, they can further (d) adjust the model's attention to a keyword or (e) directly inpaint the image.

introduce the iterative creation process with version control in PromptCharm (Sec. 4.4).

4.1 Text Prompt Refinement, Suggestion, and Exploration

Automated prompt refinement. To help users refine their initial input prompts, PromptCharm leverages a state-of-the-art prompt optimization model released by Microsoft, *Promptist* [24]. Promptist is designed to rephrase users' input prompts while retaining their original intentions. It is based on the GPT-2 architecture and was initially trained using a dataset that consisted of pairs of user input prompts and prompts refined by engineers. After supervised training, Promptist was then fine-tuned through reinforcement learning to optimize the prompt for generating visually pleasing images for *Stable Diffusion*. PromptCharm uses a pre-trained Promptist released by the authors [3].

In PromptCharm, the user can type their own words to describe what they would like to see in their generated images in a text box (Fig. 3 ⓐ). When the user click on the button PROMPT , PromptCharm will refine this input prompt with Promptist (Fig. 3 ⓐ). The refined prompt will show up in the middle text

box for the user to compare with the initial prompt. When the user clicks on the button DIFFUSE , the diffusion model will generate a new image (Fig. 3 ⓑ).

Suggesting popular modifiers. Previous studies have discussed the importance of *modifiers* (keywords that have significant effects on the generated image's style and quality) and their impacts [36, 45]. To assist users in efficiently exploring different modifiers and image styles, PromptCharm leverages a data-mining method to extract popular modifiers from a dataset of text-to-image prompts, *DiffusionDB* [67]. PromptCharm first applies the CountVectorizer algorithm [47] to extract top frequent modifiers from the *DiffsuionDB*. Given that a modifier may consist of several words (tokens), we consider n-gram phrases during our mining process, where $n = 1, 2, 3$. Finally, PromptCharm removes modifiers that only include "stop words" and sorts them according to the frequency.

When the user clicks on a token in the refined prompt in PromptCharm, a menu with four different options (**Delete**, **Replace**, **Attention**, and **Explore**) will pop up (Fig. 3 ⓑ). When the user clicks on **Replace**, the top-3 image modifiers mined from DiffusionDB [67] that provide the most similar and dissimilar art effects will show up in a drop-down list. The user can then choose

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[3]https://huggingface.co/microsoft/Promptist
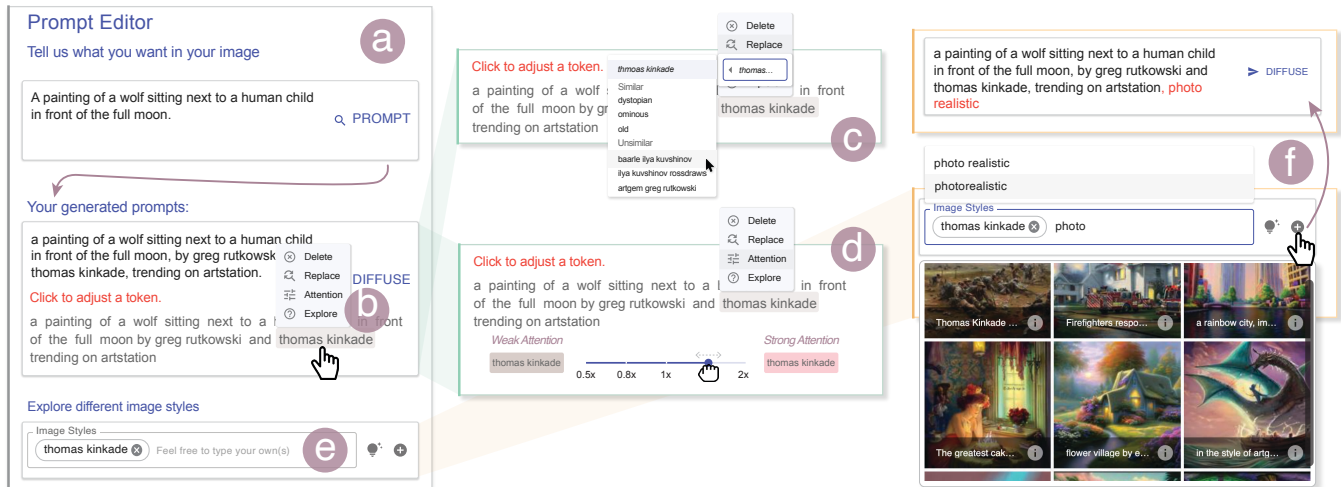
Figure 3: **PromptCharm** provides (a) automated prompt refinement and (b) prompt editing in the *prompting view*. The user can (c) replace a modifier with similar/dissimilar styles, (d) adjust the model's attention to a keyword, or (e) explore popular modifiers and (f) append them to the prompt.

to replace the selected modifier with one of them (Fig. 3 ⓒ). Note that the similarity between two image modifiers is calculated based on the cosine distance between their embedding obtained from the diffusion model's *text encoder*. When the user clicks on **Attention**, a slider will pop up for the user to adjust the model's attention to the selected keyword(s) (Fig. 3 ⓓ). We will introduce the details of the model's attention adjustment in Sec. 4.2. When the user clicks on **Explore**, the selected keyword(s) will be added to the bottom text field for further exploration (Fig. 3 ⓔ).

Image Style Exploration. In addition to replacing with similar/dissimilar image styles, the user can further explore and pick their own choices in PromptCharm (Fig. 3 ⓔ). PromptCharm displays popular image modifiers in a drop-down list (Fig. 3 ⓕ). The user can select from these popular modifiers, type a few new modifiers, or select from the prompt. After entering a few modifiers, the user can click on the "bulb" 💡 icon to search for images that include these modifiers from DiffusionDB [67]. The search results will be displayed in a pop-up grid. The user can then hover over a specific image of interest to check its complete text prompt. If the user is satisfied with the selected modifiers, they can click on the "add" ➕ icon. These modifiers will be appended to the prompt in the middle text box (Fig, 3 ⓕ).

4.2 Model Attention-based Explanation and Refinement

Model attention visualization. The attention mechanism is the most important component in the transformer models for the purpose of capturing semantic relationships among different tokens/pixels. The Stable Diffusion model, as a multi-modal model, leverages a *cross-attention* mechanism to unify the model's attention on the input text prompt and the generated image. The cross-attention scores can further be used to interpret the model's generation [59]. Therefore, considering the user might be curious about

how a generated image is correlated to their input prompts [16, 69], PromptCharm renders model explanations over both the input text prompt and the generated image with a attention-based XAI technique, *DAAM* [59]. DAAM can generate heat-map explanations over a stable diffusion model's generated image. Given a specific word from the input prompt, DAAM aggregates the model's cross-attention scores across layers and projects it to the generated image. The attention score of each token is further used to represent a token's saliency in PromptCharm to help users understand its importance towards the generation.

PromptCharm visualizes the model's attention in two ways: First, each token in the prompt is colored according to its saliency (Fig. 4). The higher importance a token has contributed to the generation, the darker background color it is assigned (Fig. 4 ⓑ). Second, when the user hovers over a token, PromptCharm will highlight particular parts of the image that are strongly related to this token during generation (Fig. 4 ⓒ).

Finally, PromptCharm can also help users interpret the correlations among different tokens in the text prompt. Given a selected token from the prompt, PromptCharm leverages a neuron activation analysis to extract a set of tokens that have similar contributions to the generated images [2]. When the user hovers over a token in PromptCharm (Fig. 4 ⓒ), the corresponding set of similar tokens will be highlighted with a different background color.

Model attention misalignment. Given a prompt, a model's attention is normally automatically calculated. However, previous studies have shown that a transformer model's calculated attention could be massively misaligned with the user's intention [20, 32]. Specifically, for text-to-image generation, the generated image's content could be inconsistent with the text prompt. Fig. 4 ⓓ shows an example of such attention misalignment. In this example, the original image (left one) misses the object "human child" in the text prompt while rendering an extra object of "wolf". To address this, PromptCharm uses an interactive design that allows users to
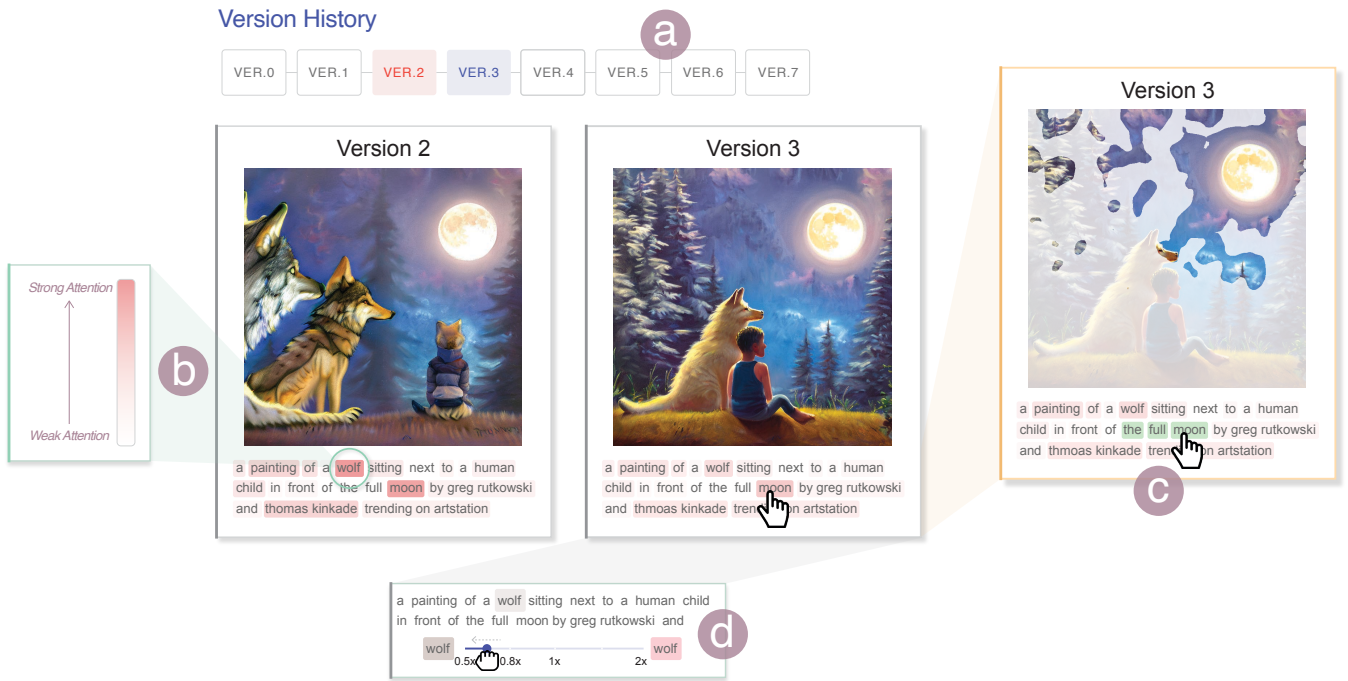
Figure 4: PROMPTCHARM provides version control with XAI feedback to help users iteratively improve their creations. (a) The user can efficiently switch between different versions. (b) The user can also observe the model's attention to each token. (c) The user can further hover over a token to check the corresponding parts in the generated image. (d) Once the user notices any "over-attending", they can directly adjust the attention to specific keywords. For example, by adjusting the attention of the word, "wolf", the model avoids mis-attending to the "human child" during the generation.

adjust the model's attention to keywords in the prompt through a slider (Fig. 4 ⓓ). Such design is highly inspired by the recent studies on aligning human's attention with the transformer model's attention [26, 62, 63]. As depicted in Fig. 4 ⓓ, by decreasing the model's attention to the "wolf", the model then correctly generate an image with one "wolf" and one "human child."

Model attention adjustment. To adjust the model's attention, PROMPTCHARM utilizes the *hooking* technique. The hooking technique originates from the software instrumentation, which allows a developer to do run-time modification over a running software process. PROMPTCHARM places hooks on all l *cross-attention layers* of a given stable diffusion model without modifying its architecture. Algorithm 1 further depicts PROMPTCHARM's model attention adjustment process. Suppose the input prompt is $\mathbf{x} = [x_1, x_2, \ldots, x_n]$, where x_j denotes the jth token. Given a set of user-selected tokens $\tilde{\mathbf{x}}$ subject to attention adjustment with corresponding adjustment factors γ, the algorithm first extracts the unaltered output S^i at the ith cross-attention layer (Line 3). Then, for each token x_j that is subject to attention adjustment, PROMPTCHARM multiplies the cross-attention output at jth token S_j^i with the user-defined factor γ_j (Line 5:10). The new text feature $\mathcal{F}^i$ is then calculated based on the altered cross-attention output (Line 11). This process loops until the model $\mathbf{M}$ finishes all l layers' inferences. During the user study, we set the maximum and minimum values of γ_j as 2 and 0.5 to avoid over-attending or completely miss-attending.

Algorithm 1: The algorithm of adjusting a diffusion model's attention.

Input: the stable diffusion model SD with l cross-attention layers, the input text prompt $\mathbf{x}$ of n tokens, the list of tokens subject to adjustment $\tilde{\mathbf{x}}$, the list of attention adjustment factors γ
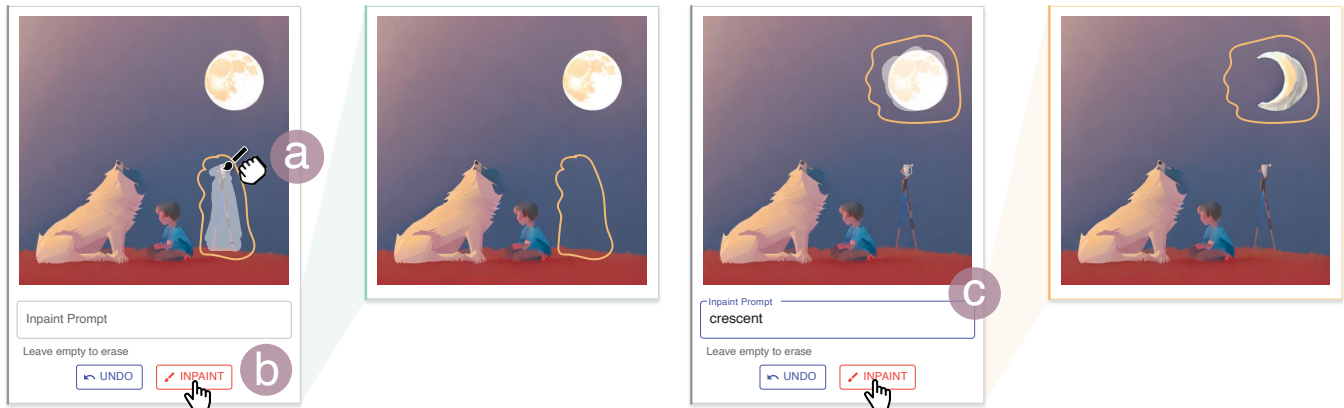
Output: the adjusted model attention S^l

1   $\mathcal{F}^0 \leftarrow$ intial feature;
2   **for** i *in* $1, \ldots, l$ **do**
3     $S^i \leftarrow$ cross_attention($SD, \mathcal{F}^{i-1}$);
4   **for** j *in* $1, \ldots, n$ **do**
5   **if** x_j *in* $\tilde{\mathbf{x}}$ **then**
6         $S_j^i \leftarrow S_j^i \times \gamma_j$;
7   **else**
8         $S_j^i \leftarrow S_j^i$;
9   **end**
10   **end**
11     $\mathcal{F}^i \leftarrow$ FFN($\mathcal{F}^{i-1}, S^i$);
12   **end**
13   **return** S^l;

Figure 5: The user can (a) mask the undesired areas in a generated image then (b) re-generate these areas in PromptCharm. (c) The user can further provide text prompts to guide the inpainting process.

4.3 Direct Manipulation via Inpainting and Masked Image Generation

In addition to *Attention Adjustment*, PromptCharm further supports refining AI-generated images through *image inpainting*. The purpose of this image inpainting feature is to allow users to re-render the small undesired areas in a generated image without further crafting the prompt. This is highly motivated by the idea of direct manipulation [56, 57]. To achieve this, we use the stable diffusion model with the image inpainting pipeline [4].

To inpaint an image, the user can brush over the area of a generated image I that they would like to re-generate to create a mask M in PromptCharm (Fig. 5 (a)). Given the image I and a mask M, when the user clicks on the INPAINT button, PromptCharm will render a new image I' where only pixels masked by M would be changed (Fig. 5 (b)). The user can further provide a text prompt $\mathbf{x}_{inpaint}$ they would like to incorporate in guiding the inpainting process by typing in the text box (Fig. 5 (c)). If $\mathbf{x}_{inpaint}$ is not given, the inpainting will be solely guided by the unmasked areas of the image.

4.4 Iterative Creation with Version Control

PromptCharm integrates a version control component to assist users in keeping track on their generated images. Each version of the generated images is displayed with the corresponding model explanations (Fig. 4). When the user clicks on one or multiple specific versions, the corresponding generated images and model explanations will show up (Fig. 4 (a)). The user can switch between different versions to examine their changes over different iterations. By default, PromptCharm presents two versions at the same time to help users compare the prompts and generated images side-by-side.

4.5 Implementation

We implemented and deployed PromptCharm as a web application. The user interface of PromptCharm is implemented with Material UI [5]. The back-end of PromptCharm is based on Python Flask.

All machine learning models are implemented with PyTorch [6] and Transformers [7]. For the diffusion model, we use the Stable Diffusion v2-1 [8]. During user studies, PromptCharm ra on a server with two NVIDIA A5000 GPUs.

5 USAGE SCENARIO

Suppose Alice is a novice user who would like to use the Stable Diffusion model to create an image. The image in her mind features the following content: "*a wolf sitting next to a human child in front of the full moon.*" However, upon entering this prompt, she discovers that the model's generated result does not align with the image she envisions. Specifically, she observes that the "human child" is not positioned correctly in the image (Fig. 6a). Additionally, she finds that her generated image lacks a sense of aesthetics. Alice then searches for relevant tutorials on the Internet. In her quest for text-to-image prompt examples on the Internet, Alice encounters numerous online resources. Nevertheless, she finds it cumbersome to experiment with various examples. Therefore, Alice decides to give PromptCharm a try.

Alice first checks the *Prompting View*, where she can articulate her requirements within a designated text box (Fig. 2 (a)). By clicking on the button PROMPT, PromptCharm autonomously generates a fresh prompt and presents it in another text box for her to further refine (Fig. 2 (b)). Alice observes that this generated prompt incorporates a few additional modifiers, such as "by greg rutkowski", "thomas kinkade", and "trending on artstation." She ponders how these modifications might enhance the resulting image. Subsequently, she opts to generate a new image by clicking on the button DIFFUSE. The new image shows up on the right side of the interface (Fig. 2 (c)) after the model finishes generation. Alice is pleased to note that the newly generated image exhibits substantial improvement in terms of the visual effects (Fig. 6b).

Nevertheless, she observes that the model fails to include the "human child" in the image and, intriguingly, includes multiple instances of the "wolf" object. Therefore, Alice resolves to refine

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[4]https://huggingface.co/docs/diffusers/api/pipelines/stable_diffusion/inpaint
[5]https://mui.com

[6]https://pytorch.org
[7]https://github.com/huggingface/transformers
[8]https://huggingface.co/stabilityai/stable-diffusion-2-1

| (a) Iteration 1 | (b) Iteration 2 | (c) Iteration 3 | (d) Iteration 4 | (e) Iteration 5 |

Figure 6: An example scenario of iteratively improving an image creation featuring "*a wolf sitting next to a human child in front of the full moon.*"

her prompt with PromptCharm's assistance to rectify her image. Alice discerns that the word "wolf" has a very high model attention value (Fig. 4 ⓓ). When she hovers over the word "wolf", a large portion of the image is highlighted. She interprets the model may probably over-attend to the word "wolf". Therefore, she clicks on the word "wolf" and select the **Attention** option. She proceeds to reduce the model's attention to this word by a factor of 0.5 before regenerating the image (Fig. 4 ⓓ). As a result, the image now accurately features both the "human child" and the "wolf" objects (Fig. 6c).

Alice is now much more satisfied with the image she has created. She ponders which modifier has contributed to the enhanced visual effects. She clicks on the modifier "thomas kinkade" and selects the **Explore** option. In the ensuing pop-up panel (Fig.3 ⓕ), she discovers quite a few examples from the database that exhibit similar visual effects to her generated image. This exploration provides Alice with a rudimentary understanding of the image's style. She believes the modifier "thomas kinkade" has contributed to such special atmosphere of the generated image. Nevertheless, her curiosity prompts her to experiment with other diverse image styles. Therefore, she selects the **Replace** option (Fig. 3 ⓒ). In a drop-down list, she opts to replace the modifier "thomas kinkade" with a dissimilar style "baarle ilya kuvshinov".

After exploring this new style, Alice finds herself more inclined toward this fresh aesthetic. Alice renders another new image (Fig. 6d). This time, the image aligns closely with her expectations, save for a minor flaw—an additional object on the right side of the image. However, she refrains from modifying her prompt to rectify this issue, as such adjustments could potentially impact other areas in the image. Alice then attends to the *inpainting view* of PromptCharm. She clicks on the button INPAINT to open the inpainting canvas. Alice then brushes over the area that she would like to re-generate (Fig. 5 ⓐ). Following the inpainting process, the generated image now aligns better with her expectations (Fig. 6e). By clicking on the label "VER.0" (Fig. 4 ⓐ), Alice compares her most recent iteration with her initial creation. She observes a significant improvement in terms of image quality and visual effects.

6 USER STUDY 1: CLOSE-ENDED TASKS

To evaluate the usability and effectiveness of PromptCharm, we conducted a within-subjects user study with 12 participants from different levels of experience with generative AI and text-to-image

generation models. To better understand the value of proposed features in PromptCharm, we compared PromptCharm with two variants of PromptCharm as the baselines by disabling interactive features. Specifically,

- **Baseline**. The baseline includes a plain text editor for users to write their prompts as well as the version history.
- **Promptist**. In addition to the features in Baseline, we further introduce the *Promptist* model [24] to help users refine their prompts. This is to simulate the situation in which users only have a fully automated model for prompt engineering.

6.1 Methods

6.1.1 Participants. We recruited 12 participants through mailing lists of the ECE and CS departments at a research university.[9] 1 participant was an undergraduate student, 3 participants were Master students, 7 were Ph.D. students, and 1 were professional developers. Participants were asked to self-report their experience with general generative AI (e.g., ChatGPT) and text-to-image creation models (e.g., DALL-E and Midjourney). Regarding experience with general generative AI, 3 participants had 2-5 years of experience, 5 had 1 year, and 4 had less than 1 year or no experience. Regarding text-to-image generative model experience, 3 participants had 1 year of experience while the remaining had less than 1 year or no experience. All participants mentioned that they had never used any prompt engineering tools before. We conducted all user study sessions via Zoom. PromptCharm and two baselines were all deployed as web applications. Therefore, participants were able to access our study sessions from their own PCs.

6.1.2 Tasks. The goal of this study is to identify the effectiveness of PromptCharm when helping users achieve a specific image creation target. To this end, we designed three different tasks based on the prompts from *DiffusionDB* that were excluded from PromptCharm's data mining process (Sec. 4.1). Specifically, we randomly sampled 60 prompts that included animals as subjects. Then, we used the stable diffusion model to generate an image for each of the given prompts. We resolved to select three prompts that are complex, and the corresponding generated images are with good quality and visual effects. For each task, a participant was then given one of the three images as the target. The participant's goal is to replicate the given target image as similar as possible with

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[9]This human-participated study is approved by the university's research ethics office.

Table 1: User performance in Study 1 measured by SSIM [66]. Higher SSIM indicates better performance.

Conditions	Task 1		Task 2		Task 3		Overall	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Baseline	0.521	0.053	0.473	0.082	0.443	0.187	0.479	0.115
Promptist	0.707	0.079	0.529	0.017	0.487	0.043	0.574	0.111
PromptCharm	0.708	0.063	0.606	0.078	0.631	0.138	0.648	0.100

the help of an assigned tool. Note that we rewrote each prompt as the initial prompt for the participant to start with by removing all keywords related to the image's style. This is to provide a similar starting point for participants with different levels of expertise. However, participants are not required to use the initial prompt to start creation. Table A1 in the Appendix shows the details of each close-ended study task.

6.1.3 Protocol. Each user study session took about 1.5 hours. At the beginning of each session, we asked participants for their consent to record. Participants were then assigned three tasks about text-to-image creations, each of them to be completed with either **PromptCharm**, **Baseline**, or **Promptist**. To mitigate the learning effect, both task assignment order and tool assignment order were counterbalanced across participants. Before starting each task, one of the authors conducted an online tutorial to walk through and explain the features of the assigned tool. Then, participants were given a 5-minute practice period to familiarize themselves with the tool, followed by a 15-minute period to use the assigned tool to iteratively refine their image creations. After completing each task, participants filled out a post-task survey to give feedback about what they liked or disliked. Participants were also asked to answer five NASA Task Load Index (TLX) questions [25] as a part of the post-task survey. After completing all three tasks, participants filled out a final survey, where they directly compared three assigned tools. At the end of the study session, each participant received a $25 Amazon gift card as compensation for their time.

6.2 Results

In this section, we report and analyze the difference in participants' performance in Study 1 when using PromptCharm and the two baseline tools. For brevity, we denote the participants in the user study as P1-P12.

6.2.1 User Performance. We measure a participant's performance in a close-ended task by calculating the *structural similarity index* (SSIM) [66] between the generated image and the target image. We also refer readers to Fig. A1 in the Appendix for images generated by our participants. Table 1 depicts participants' performance in three different tasks. Overall, participants using PromptCharm yield the best performance on all three tasks, achieving an average SSIM of 0.648. By contrast, participants using Baseline and Promptist achieved average SSIM of 0.479 and 0.574, respectively. We further used Welch's t-test to examine the performance difference between different tools in each task. For task 1, the performance between the participants using PromptCharm and the participants using Baseline is statistically different ($p < 0.01$). However, the performance between the participants using PromptCharm and the participants

using Promptist is not statistically different ($p = 0.49$). Our further investigation shows that this task is relatively simpler (which only includes one subject in the image) compared with the other two tasks (which include multiple subjects). The automatically refined prompt could already lead to a generated image that looks close to the target image. Therefore, it is not surprising that participants using Promptist also performed well in this task. Nevertheless, we found participants using PromptCharm performed significantly better in Task 2 and Task 3 (both tasks include multiple objects in the images) compared with participants using Baseline ($p < 0.01$ and $p = 0.03$) and Promptist ($p = 0.04$ and $p = 0.03$). Participants also self-rated how similar their generated image looks compared with the target image on a 7-point Likert scale (1—Dissimilar, 7—Similar). We found that participants using PromptCharm performed significantly better (median rating: 6) compared with Baseline (median rating: 3.5, Wilcoxon signed-rank test: $p = 0.02$) and Promptist (median rating: 5, Wilcoxon signed-rank test: $p = 0.05$).

To understand why participants using PromptCharm performed better in the two challenging tasks, we analyzed the post-task survey responses and the recordings. We found that PromptCharm users' better performance could be attributed to its *multi-modal prompting support* and *rich feedback*. First, we found participants heavily relied on exploring different modifiers in PromptCharm's prompting view. The average number of modifiers explored per participant is 4.8. By exploring different art styles ahead, participants were able to gain insights from PromptCharm before generating an image (which usually takes about 30 seconds per generation in our user study). P8 commented, "*Exploring different styles [in PromptCharm] can help me understand them in the suggested prompts.*" By contrast, P9 wrote, "*I can not choose any art style from the model-refined prompt since I do not have enough expert knowledge [when using Promptist].*" Second, participants also found the attention adjustment helpful during the image refinement. Based on the recordings, the average number of attention adjustments per participant was 4.3. In the post-task survey, all participants marked the attention adjustment as helpful. P9 said, "*[PromptCharm] can precisely catch the parts that I want to improve through attention adjustment.*" Meanwhile, participants using baselines struggled with aligning the model's attention with their creative intention. P7 complained, "*sometimes, the generated image does not include the elements that I wrote in the prompt [when using Baseline].*"

We also further analyzed the impact of the initial prompt in Study 1. We found that 4 out of 12 participants did not use the provided initial prompt. Overall, these four participants achieved an average SSIM of 0.647, which is similar to the overall performance among 12 participants (average SSIM: 0.648). Therefore, we believe the initial prompt may have little effect on user performance.
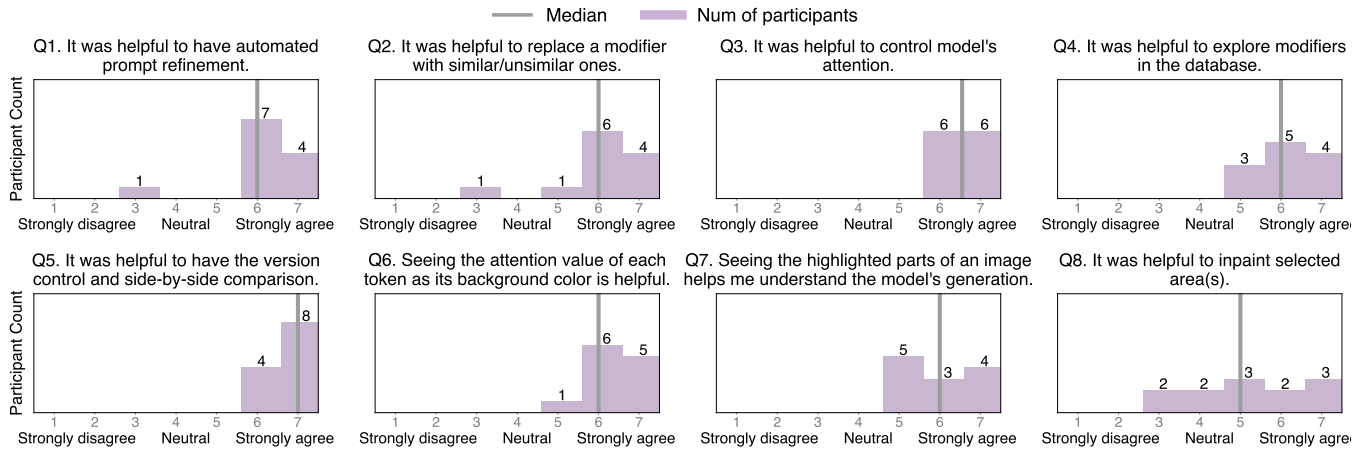
Figure 7: User's ratings on individual features of PromptCharm in Study 1.

6.2.2 User Ratings of Individual Features. In the post-task survey, 9 out of 12 participants indicated that they would like to use PromptCharm for image creation in the future, while 3 participants stayed neutral. The median rating is 6 on a 7-point Likert scale (1—I do not want to use it at all, 7—I will definitely use it). Participants also rated the key features of PromptCharm in the post-task survey. As shown in Fig. 7, participants agreed most of the interactive features in PromptCharm (median rating ≥ 6) were helpful except stayed neutral about *image inpainting* (median rating: 5). The most appreciated features in PromptCharm is the *model attention adjustment*, where the median rating is 6.5. P12 commented, "*[PromptCharm] can help me get better images as I imagined by adjusting the attention of different words in the prompt.*" Besides, all participants also agreed that "*it was helpful to have the version control and side-by-side comparison.*" 11 out of 12 participants agreed that "*seeing the attention value of each token as its background color was helpful.*" The median rating is 6. P8 said, "*PromptCharm can provide the information about the effect of each token [through attention visualization]. Then I know how to adjust the attention.*" Regarding *image inpainting*, participants highlighted the need of performance improvement. For example, when trying to inpaint a relatively large area in the image, P11 found that the inpainted content did not fit the original image's background well. P11 thus commented, "*while generally it is acceptable, sometimes the inpainting effect is not ideal.*"

6.2.3 Cognitive Overhead. Fig. 8 shows participants' ratings on the five cognitive factors of the NASA TLX questionnaire. Though PromptCharm has more interactive features, we did not find statistical evidence indicating that participants using PromptCharm experienced more mental demand compared with the participants using Baseline (Wilcoxon signed-rank test: $p = 0.47$) and Promptist ($p = 0.63$). However, participants using PromptCharm felt they had better performance while experiencing less frustration compared with the participants using Baseline (Wilcoxon signed-rank test: $p < 0.01$, $p < 0.01$) and Promptist (Wilcoxon signed-rank test: $p = 0.04$, $p = 0.03$). In terms of effort and hurry, participants felt they experienced less hurry and spent less effort when
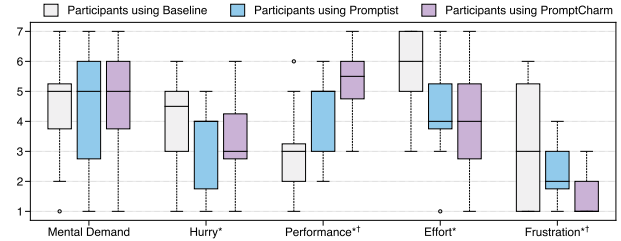

Figure 8: NASA Task Load Index Ratings in Study 1. Entries with a star (*) mean the mean difference is statistically significant ($p < 0.05$) between PromptCharm and Baseline. Entries with a dagger (†) mean the mean difference is statistically significant ($p < 0.05$) between PromptCharm and Promptist.

using PromptCharm compared with using Baseline (Wilcoxon signed-rank test: $p = 0.03$ and $p < 0.01$). However, such differences between using PromptCharm and Promptist are not significant (Wilcoxon signed-rank test: $p = 0.61$ and $p = 0.22$).

6.2.4 User Preference and Feedback. In the final survey, participants self-reported their preference among PromptCharm, Baseline, and Promptist. All 12 participants found that PromptCharm was the most helpful among three tools (median ranking: 1) and they preferred to use it in practice (median ranking: 1). We coded participants' responses in the final survey and found their preference mainly come from two sources. First, 9 out of 12 participants highlighted the contribution of the *attention adjustment*. P11 wrote, "*in PromptCharm, I can adjust the attention of each word and thereby refine my images directly.*" Second, 8 out of 12 participants mentioned that *image style exploration* helps them understand a particular style without actually generating an image. P10 commented, "*with PromptCharm, I can easily know the reason why I choose an image style keyword even though I do not have such domain knowledge.*"

Participants also mentioned the limitations in the current version of PromptCharm in the final survey. 3 out of 12 participants mentioned the performance of inpainting could be further improved. 2
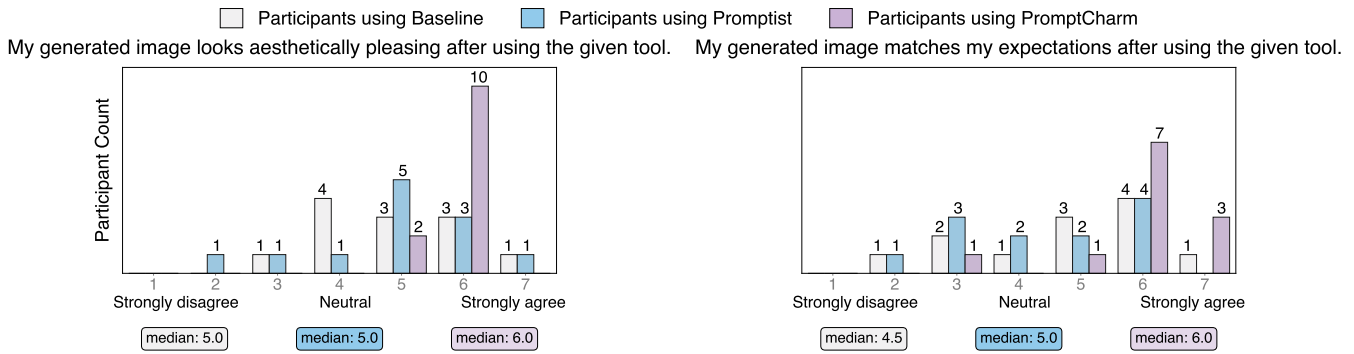
Figure 9: User's self-assessments of their performance in Study 2.

out of 12 participants suggested adding an interactive feature that users can directly drag a subject to a specific position.

7 USER STUDY 2: OPEN-ENDED TASKS

We conducted another within-subjects user study with another 12 participants to evaluate PromptCharm's usability when performing open-ended tasks. We compared PromptCharm with the same baselines (Baseline and Promptist) as Study 1 (Sec. 6). We also followed the same protocol as Study 1 (Sec. 6.1.3).

7.1 Methods

7.1.1 Participants. We recruited 12 participants through mailing lists of the ECE and CS departments at a research university [10]. 6 participants were Master students, 6 were Ph.D. students. Participants were asked to self-report their experience with general generative AI (e.g., ChatGPT) and text-to-image creation models (e.g., DALL-E and Midjourney). Regarding general generative AI, 1 participant had 2-5 years of experience, 7 had 1 year, and 4 had less than 1 year or no experience. Regarding text-to-image creation experience, 3 had 1 year of experience, and 9 had less than 1 year or no experience. All participants mentioned that they had never used any prompt engineering tools before. We conducted all user study sessions via Zoom. PromptCharm and two baselines were again deployed as web applications. Therefore, participants were able to access our study sessions from their own PCs.

7.1.2 Tasks. Different from Study 1, Study 2 does not assign the participants with the target images. For each task, we provided a participant with subject(s) to be included in the image. We designed three different image scenes and each of them features one or multiple subjects. The participants were asked to create an image in each task given one of the three image scenes with the help of an assigned tool based on their own creative ideas. Though giving specific image subjects might limit a participant's creative freedom, it yielded a more controlled experiment for assessing a tool's usability. Table B2 in the Appendix shows the details of each open-ended task in our user study.

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[10]This human-participated study is approved by the university's research ethics office.

7.2 Results

In this section, we report and analyze the difference in participants' performance in Study 2 when using PromptCharm and the two baseline tools. For brevity, we denote the participants in Study 2 as P13-P24 to distinguish them from Study 1.

7.2.1 User Performance. As there is no objective measurement for user performance in open-ended tasks, we asked participants to self-report their assessments to the quality of their generated images in the post-task survey in Study 2. We also refer readers to Fig. B2 in the Appendix for images generated by our participants. In the post-task survey, we asked participants to answer the following two 7-point Likert scale (1—Strongly disagree, 7—Strongly agree) questions: (1) *my generated image looks aesthetically pleasing after using the assigned tool*, and (2) *my generated image matches my expectations after using the assigned tool*. Fig. 9 shows participants' assessments when using PromptCharm and two baseline tools. We found that participants felt their generated images were more aesthetically pleasing (median rating: 6) and closer to their expectations (median rating: 6) when using PromptCharm compared with using either Baseline (median ratings: 5 and 4.5) or Promptist (median ratings: 5 and 5). In terms of aesthetically pleasing, there is a statistically significant performance difference between the participants using PromptCharm and Baseline (mean difference: 5.8 vs. 4.9, Wilcoxon signed-rank test: $p = 0.02$), as well as between PromptCharm and Promptist (mean difference: 5.8 vs. 4.9, Wilcoxon signed-rank test: $p < 0.01$). In terms of matching expectations, there is also a statistically significant performance difference between PromptCharm and Baseline (mean difference: 5.9 vs. 4.4, Wilcoxon signed-rank test: $p = 0.02$), as well as between PromptCharm and Promptist (mean difference: 5.9 vs. 4.8, Wilcoxon signed-rank test: $p = 0.04$).

We further analyzed participants' qualitative responses in the post-task survey and the video recordings and compared the results with Study 1. While similar features such as *exploring modifiers* and *model attention adjustment* had contributed to the success, we found participants in Study 2 shared different user behaviors. First, when exploring image modifiers, participants in Study 1 usually ended up selecting only two or three keywords. Then, they would try out different combinations and replacements to make the generated
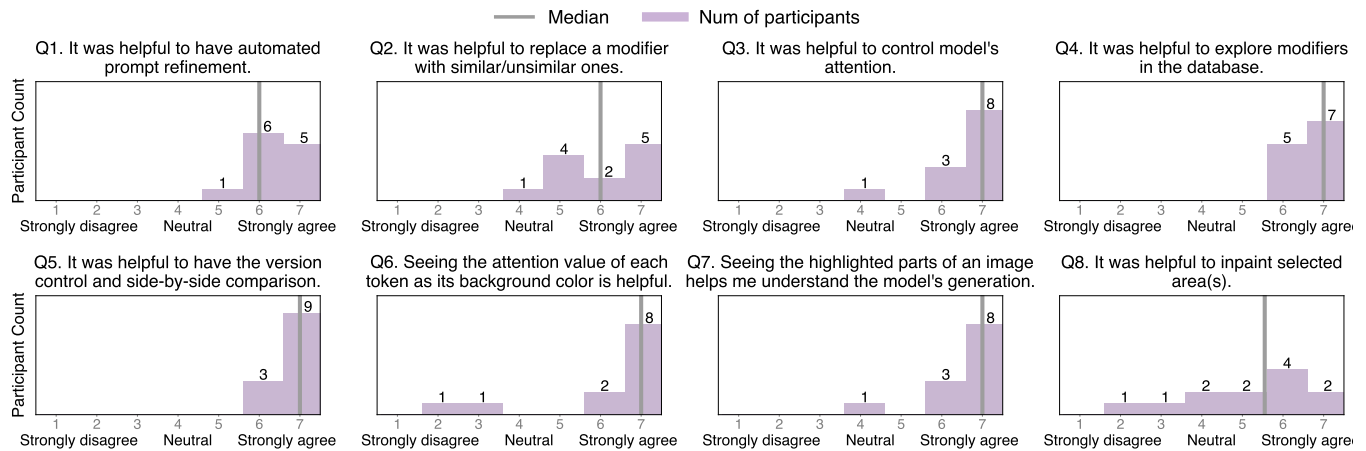
Figure 10: User's ratings on individual features of PromptCharm in Study 2.

image look closer and closer to the target one. By contrast, participants in Study 2 explored and selected many more modifiers (7.3 modifiers on average) and experimented with more different image styles. As a result, 8 out of 12 participants explicitly mentioned in the post-task survey that PromptCharm enables them to discover a diverse set of image styles. P22 commented, "*[PromptCharm] gives me a lot of different image style suggestions. I can generate my image more freely.*" By contrast, participants using two baselines had a hard time selecting image styles. P15 said, "*[when using Baseline,] it was easy for me to describe an image scene. But it was hard for me to provide keywords about image styles.*" Second, since participants were given more freedom in Study 2, we found that they tended to write longer and more complex prompts. In this case, with the help of PromptCharm's model attention adjustment, participants did not need to worry about the model losing attention to subjects after appending a lot of image modifiers. For instance, P20 wrote a long prompt with more than 60 tokens for Task 1 and found that the generated image missed the object "cat." Such a problem was then easily fixed by P20 with model attention adjustment to the word "cat." P20 then commented, "*[attention adjustment] makes things easier. I can now focus on selecting image styles.*"

7.2.2 User Ratings of Individual Features. 11 out of 12 participants indicated that they would like to use PromptCharm for image creation in the future in the post-task survey, while 1 participant stayed neutral. The median rating is 6 on a 7-point Likert scale (1—I do not want to use it at all, 7—I will definitely use it). Regarding the individual features, all participants agreed that *it was helpful to explore modifiers in the database* (median rating: 7). P16 wrote, "*[in PromptCharm], I can easily understand the meaning of each keyword by exploring them.*" All participants also agreed that the *version control* was helpful (median rating: 7). Furthermore, 11 out of 12 participants also agreed that *it was helpful to control model's attention.* P13 commented, "*I can simplify the complex prompting work by directly adjusting the attention.*"

7.2.3 Cognitive Overhead. Fig. 11 presents participants' assessments to the five cognitive factors of the NASA TLX questionnaire
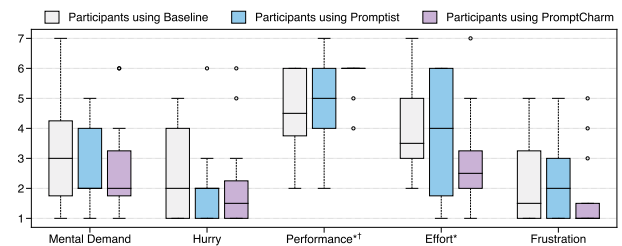

Figure 11: NASA Task Load Index Ratings in Study 2. Entries with a star (*) mean the mean difference is statistically significant ($p < 0.05$) between PromptCharm and Baseline. Entries with a dagger (†) mean the mean difference is statistically significant ($p < 0.05$) between PromptCharm and Promptist.

in Study 2. As shown in Fig. 11, we did not find significant differences between PromptCharm and two baselines regarding mental demand (Wilcoxon signed-rank test: $p = 0.21$, $p = 0.42$), hurry (Welch's t-test: $p = 0.25$, $p = 0.55$), and frustration (Wilcoxon signed-rank test: $p = 0.18$, $p = 0.19$). These results indicate that more interaction in PromptCharm did not introduce additional burdens or learning barriers to users in open-ended tasks. Moreover, when using PromptCharm, participants significantly felt they had better performance compared with using Baseline (Wilcoxon signed-rank test: $p = 0.01$) and Promptist (Wilcoxon signed-rank test: $p = 0.02$). Participants also felt they were spending less effort when using PromptCharm compared with using Baseline (Wilcoxon signed-rank test: $p = 0.04$), while such difference is not significant between PromptCharm and Promptist (Wilcoxon signed-rank test: $p = 0.18$). We also found that Study 2's participants experienced less mental demand and spent less effort compared with Study 1's participants (Fig. 8). A plausible explanation is participants might feel less stressed when performing the open-ended tasks (Study 2).

7.2.4 User Preference and Feedback. In the final survey, 11 out of 12 participants found that PromptCharm was the most helpful

among three conditions (median ranking: 1). Besides, all participants indicated that they preferred to use PromptCharm more compared with the two baselines (median raking: 1). After coding the participants' responses, we identified two different themes that led to such preference. First, participants felt they were directly interacting with the model when using PromptCharm. P18 said, "*I could modify the prompt in a way where it tells me I'm interacting directly with the model. While for the other two, I had to guess a lot of things without knowing where the model is putting more importance.*" P16 commented, "*I can gain more control over the image generation process [when using PromptCharm]. Thus, I felt more confident about how to generate an expected image.*" Second, participants also appreciated the rich feedback loop in PromptCharm as it yielded a higher efficiency. P21 wrote, "*[in PromptCharm], I have more choices when I need to refine my image, e.g., I can either change the attention or directly erase the elements that I do not want. This is the most time-saving among the three tools.*" P14 said, "*exploring different modifiers save my time. I can check different image styles without actually using the model to generate one.*"

Participants also gave their feedback about the potential improvements of PromptCharm in the post-task and final surveys. In addition to those discussed in Study 1 (Sec. 6.2.4), 2 out of 12 participants further mentioned the need for textual explanations for different image modifiers in PromptCharm's *image style exploration*.

8 DISCUSSION

The rise of generative models and prompt engineering have significantly influenced many fields and domains. Our user study results indicate that even novice users can use the stable diffusion model to create aesthetically pleasing images with rich interactive prompt engineering support. Therefore, it is worth continuing to investigate new interaction designs to assist novice users in prompt engineering. This section discusses the implications derived from our system design and user studies, as well as limitations and future work.

8.1 Assisting Effective Prompt Engineering with Model Explanations

When designing human-AI interaction, an important guideline is *making clear why the system did what it did* [3]. However, to the best of our knowledge, there is little investigation into how to provide model explanations for prompt engineering. During our user studies, we particularly found that the lack of proper model explanations may lead to user frustration. For example, when working on Task 3 in Study 2 without model explanations (Baseline), P18 commented, "*I could not figure out why the model keeps generating multiple penguins until I manually changed the word 'playing' to 'rolling'. Then I realized that the model might have a high attention on this word. I could have found this easily if I have any support like attention visualization.*" When using PromptCharm, by observing the model's attention to different keywords in the prompt, the user can quickly identify if the model has missed any keywords during the generation. As a result, the user can refine their prompts

and images in a more targeted manner. For instance, they can directly increase the model's attention to a keyword if they found this keyword has been misattended by the model during the generation.

8.2 Enriching User Feedback Loop in Prompt Engineering

Prompting has proven to be a valuable asset in human-AI collaboration, as large language models can now effectively comprehend natural language instructions from users and directly translate them into actions. However, when addressing specific tasks, such as text-to-image creation, relying solely on prompting as the interface between the user and generative models is insufficient. On the one hand, the model should help users understand how their feedback has been incorporated during the generation. On the other hand, the model should provide flexible ways to elicit user feedback. Ultimately, the goal is to create images that better align with the user's creative intent, rather than writing complex and long prompts. The design of PromptCharm is highly influenced by one of the design principles for mixed-initiative user interfaces [28]—*providing mechanisms for efficient agent-user collaboration to refine results.* PromptCharm enables multi-modal prompt refinement, including image style exploration, model attention visualization, attention adjustment, and image inpainting. According to our user study results, such mixed-initiative design led to better user performance in both close-ended and open-ended tasks.

8.3 Addressing Conceptual Gaps

Our user studies reveal significant *conceptual gaps* when novice users write prompts for image creation. In many cases, users have a clear image style in mind, but they find it challenging to articulate it in a prompt. This difficulty becomes more pronounced when it comes to selecting effective keywords (i.e., modifiers) for the stable diffusion model. Broadly speaking, this issue resembles one of the six learning barriers in designing end-user programming systems—*selection barriers* [30], where *users know what they want the computer to do, but they do not know what to use.* To address this, PromptCharm supports *image style exploration.* The user can efficiently browse popular image style keywords and further contextualize them by retrieving relevant images from a large database. As a result, participants performed better when using PromptCharm to solve the close-ended tasks, which require them to replicate a particular image and its style. Such a design also facilitates users understanding the model-refined prompts. For instance, when talking about the automated prompt refinement, P15 said, "*initially, I have no ideas about the meaning of the words it added, so I won't know how to change the prompt to generate a picture that I want.*" P15 continued to comment, "*however, I found PromptCharm addressed my need by supporting me explore the generated prompts' keywords with example pictures from the database.*"

8.4 Exploration vs. Exploitation

The open-ended tasks and the close-ended tasks in our user study can represent two modes of interaction: *exploration* and *exploitation.* In the exploitation mode, users have a clear understanding of their objectives. During Study 1 (close-ended tasks), we observed that participants spent a considerable amount of time comparing their

generated images with the target images before making adjustments to the prompts or refining the images. For instance, when they found the generated image's art style was obviously different from the target image, they first analyzed which keyword in the prompts had contributed to the distinct style by examining the model's attention. Once they identified such keyword(s), they proceeded to replace it with another keyword that better matched the target style by selecting modifiers in PROMPTCHARM. In the exploration mode, users usually do not have a clear objective. In Study 2 (open-ended tasks), participants often started by formulating a basic prompt that included the image scene they had in mind. Subsequently, they focused on the ideation of the image styles by exploring and combining different and diverse image styles in PROMPTCHARM. Once they determined their desired image style, the process of refining images transitioned back to the exploitation mode. Such observation of the different modes' user behavior is similar to the previous studies on how programmers interact with AI programming assistants in *acceleration* mode and *exploration* mode [4, 44]. Our study results further imply that PROMPTCHARM can support both modes effectively. As Louie et al. [39] pointed out, the human-AI interface for creative design should empower the user whether they have a clear creative goal in mind or not. Therefore, in future work, it is important to take *exploration-exploitation balancing* into account when designing interactive systems for prompt engineering and creative design.

8.5 User Experience vs. User Performance

PROMPTCHARM is designed for users with different levels of expertise, especially for those who had limited experience in text-to-image creation. During our user study, only 6 out of 24 participants had 1 year of experience with text-to-image creation models, while the rest of them had less than 1 year of experience. In Study 1, we found that 3 participants who had 1 year of experience had similar performance (average SSIM: 0.642) compared with the others (average SSIM: 0.649). In Study 2, 3 participants with more experience had the same performance in terms of aesthetically pleasing (median rating: 6) and expectation matching (median rating: 6) compared with the others. These results indicate that the effectiveness of PROMPTCHARM is not strongly correlated to user expertise.

8.6 Limitations and Future Work

There are several limitations in our user study design and system in addition to those pointed out by our user study participants as described in Sec. 6.2.4 and Sec. 7.2.4.

User Study Design. In our current open-ended study, we manually designed three image scenes for participants. However, though such a design provides a more controllable set-up for evaluation, this may limit the participants' creative freedom. In future work, the open-ended study can be improved with the free-form usage of PROMPTCHARM [18]. Then, to assess a user's performance, one can consider the expert evaluation. Besides, PROMPTCHARM has only been evaluated with novice users. In future work, we plan to evaluate PROMPTCHARM's effectiveness with experts in text-to-image creation.

Generalization Issue. Though we have only evaluated PROMPTCHARM on the *Stable Diffusion*, we believe the design of

PROMPTCHARM can generalize to other open-source text-to-image generation models, e.g., CogView [13], VQGAN+CLIP [11]. Evaluating PROMPTCHARM's usability with different text-to-image models may worth investigating in future work. To reuse PROMPTCHARM for close-source models such as DALL-E [12] and Midjourney [13], alternative design for *attention adjustment* and *model explanations* need to be proposed. For instance, an alternative approach of *attention adjustment* could be adding corresponding instructions in the prompts. For *model explanations*, one may consider model-agnostic XAI methods, e.g., LIME [52] and SHAP [40].

Large-scale Exploration. In the current design, PROMPTCHARM can only assist users in examining one generated image per version. This is because the main goal of PROMPTCHARM is to help novice users iteratively improve their creation based on the previous generation. Nevertheless, in future work, PROMPTCHARM could be improved to support experienced users exploring a large batch of generation (e.g., 30 images per prompt) simultaneously. To achieve this, specific design for image layout, e.g., organizing images by clustering based on the colors [18] or semantic similarity [5] may be leveraged.

Alternative Algorithms and Design. In the current version of PROMPTCHARM, we use *Promptist* [24], a GPT-2 based model fine-tuned through reinforcement learning for automated prompt refinement given its popularity and availability. However, other different prompt refinement methods, e.g., gradient-based prompt search [70], few-shot prompting with powerful LLMs (GPT4) [5] might yield better prompting results. Besides, our current inpainting method sometimes did not provide the user intended results, especially when the inpainted area is large (Sec. 6.2.2). This may be improved with the alternative design and models, e.g., *prompt-to-prompt* [27], a method that uses the cross-attention map to enable content-preserving inpainting with the stable diffusion model.

9 CONCLUSION

In this paper, we present PROMPTCHARM, a mixed-initiative system that assists novice users in text-to-image generation through multi-modal prompting and refinement. PROMPTCHARM provides automated prompt refinement to help users optimize their input text prompt with the help of a SOTA model, *Promptist*. The user can further improve their prompt by exploring different image styles and keywords within PROMPTCHARM. To support users in effectively refining their images, PROMPTCHARM provides model explanations through model attention visualization. Once the user notices any unsatisfactory parts in the image, they can refine it by adjusting the model's attention to keywords, or masking those areas and re-generate it through an image inpainting model. Lastly, PROMPTCHARM integrates the version control to enable users to easily track their creations. Through a user study of 12 participants including close-ended tasks, we found that participants using PROMPTCHARM can create images that closely resembled the given target images when compared to two baseline methods. In another user study of 12 participants featuring open-ended tasks, participants using PROMPTCHARM felt that their generated images were

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[11]https://github.com/nerdyrodent/VQGAN-CLIP
[12]https://openai.com/dall-e-2
[13]https://www.midjourney.com

more aesthetically pleasing and better matched their expectations compared with using two baselines. In the end, we discuss the design implications from PromptCharm and propose several interesting future research opportunities.

ACKNOWLEDGMENTS

REFERENCES

[1] 2023. Stable Diffusion Web UI. https://github.com/AUTOMATIC1111/stable-diffusion-webui. Last Release: 2023-08-30.

[2] J Alammar. 2021. Ecco: An open source library for the explainability of transformer language models. In *Proceedings of the 59th annual meeting of the association for computational linguistics and the 11th international joint conference on natural language processing: System demonstrations*. Association for Computational Linguistics, Online, 249–257. https://doi.org/10.18653/v1/2021.acl-demo.30

[3] Saleema Amershi, Dan Weld, Mihaela Vorvoreanu, Adam Fourney, Besmira Nushi, Penny Collisson, Jina Suh, Shamsi Iqbal, Paul N. Bennett, Kori Inkpen, Jaime Teevan, Ruth Kikin-Gil, and Eric Horvitz. 2019. Guidelines for Human-AI Interaction. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3290605.3300233

[4] Shraddha Barke, Michael B. James, and Nadia Polikarpova. 2023. Grounded Copilot: How Programmers Interact with Code-Generating Models. *Proc. ACM Program. Lang.* 7, OOPSLA1, Article 78 (apr 2023), 27 pages. https://doi.org/10.1145/3586030

[5] Stephen Brade, Bryan Wang, Mauricio Sousa, Sageev Oore, and Tovi Grossman. 2023. Promptify: Text-to-Image Generation through Interactive Prompt Exploration with Large Language Models. In *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology (UIST '23)*. Association for Computing Machinery, New York, NY, USA, Article 96, 14 pages. https://doi.org/10.1145/3586183.3606725

[6] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language Models are Few-Shot Learners. In *Advances in Neural Information Processing Systems*, H. Larochelle, M. Ranzato, R. Hadsell, M.F. Balcan, and H. Lin (Eds.), Vol. 33. Curran Associates, Inc., 1877–1901.

[7] Carrie J. Cai, Emily Reif, Narayan Hegde, Jason Hipp, Been Kim, Daniel Smilkov, Martin Wattenberg, Fernanda Viegas, Greg S. Corrado, Martin C. Stumpe, and Michael Terry. 2019. Human-Centered Tools for Coping with Imperfect Algorithms During Medical Decision-Making. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3290605.3300234

[8] Carrie J. Cai, Samantha Winter, David Steiner, Lauren Wilcox, and Michael Terry. 2019. "Hello AI": Uncovering the Onboarding Needs of Medical Practitioners for Human-AI Collaborative Decision-Making. *Proc. ACM Hum.-Comput. Interact.* 3, CSCW, Article 104 (nov 2019), 24 pages. https://doi.org/10.1145/3359206

[9] Siddhartha Chaudhuri, Evangelos Kalogerakis, Stephen Giguere, and Thomas Funkhouser. 2013. Attribit: content creation with semantic attributes. In *Proceedings of the 26th Annual ACM Symposium on User Interface Software and Technology (UIST '13)*. Association for Computing Machinery, New York, NY, USA, 193–202. https://doi.org/10.1145/2501988.2502008

[10] Xiang 'Anthony' Chen, Ye Tao, Guanyun Wang, Runchang Kang, Tovi Grossman, Stelian Coros, and Scott E. Hudson. 2018. Forte: User-Driven Generative Design. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3173574.3174070

[11] Lydia B Chilton, Ecenaz Jen Ozmen, Sam H Ross, and Vivian Liu. 2021. VisiFit: Structuring Iterative Improvement for Novice Designers. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (CHI '21)*. Association for Computing Machinery, New York, NY, USA, Article 574, 14 pages. https://doi.org/10.1145/3411764.3445089

[12] John Joon Young Chung and Eytan Adar. 2023. PromptPaint: Steering Text-to-Image Generation Through Paint Medium-like Interactions. In *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology (UIST '23)*. Association for Computing Machinery, New York, NY, USA, Article 6, 17 pages. https://doi.org/10.1145/3586183.3606777

[13] Ming Ding, Zhuoyi Yang, Wenyi Hong, Wendi Zheng, Chang Zhou, Da Yin, Junyang Lin, Xu Zou, Zhou Shao, Hongxia Yang, and Jie Tang. 2021. CogView: Mastering Text-to-Image Generation via Transformers. In *Advances in Neural Information Processing Systems*, M. Ranzato, A. Beygelzimer, Y. Dauphin, P.S. Liang, and J. Wortman Vaughan (Eds.), Vol. 34. Curran Associates, Inc., 19822–19835.

[14] John J. Dudley and Per Ola Kristensson. 2018. A Review of User Interface Design for Interactive Machine Learning. *ACM Trans. Interact. Intell. Syst.* 8, 2, Article 8 (jun 2018), 37 pages. https://doi.org/10.1145/3185517

[15] Patrick Esser, Robin Rombach, and Bjorn Ommer. 2021. Taming Transformers for High-Resolution Image Synthesis. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. 12873–12883.

[16] Noyan Evirgen and Xiang 'Anthony' Chen. 2022. GANzilla: User-Driven Direction Discovery in Generative Adversarial Networks. In *Proceedings of the 35th Annual ACM Symposium on User Interface Software and Technology (UIST '22)*. Association for Computing Machinery, New York, NY, USA, Article 75, 10 pages. https://doi.org/10.1145/3526113.3545638

[17] Noyan Evirgen and Xiang 'Anthony' Chen. 2023. GANravel: User-Driven Direction Disentanglement in Generative Adversarial Networks. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 19, 15 pages. https://doi.org/10.1145/3544548.3581226

[18] Yingchaojie Feng, Xingbo Wang, Kam Kwai Wong, Sijia Wang, Yuhong Lu, Minfeng Zhu, Baicheng Wang, and Wei Chen. 2024. PromptMagician: Interactive Prompt Engineering for Text-to-Image Creation. *IEEE Transactions on Visualization and Computer Graphics* 30, 01 (jan 2024), 295–305. https://doi.org/10.1109/TVCG.2023.3327168

[19] Tianyu Gao, Adam Fisch, and Danqi Chen. 2021. Making Pre-trained Language Models Better Few-shot Learners. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*. Association for Computational Linguistics, Online, 3816–3830. https://doi.org/10.18653/v1/2021.acl-long.295

[20] Noa Garcia, Yusuke Hirota, Yankun Wu, and Yuta Nakashima. 2023. Uncurated Image-Text Datasets: Shedding Light on Demographic Bias. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 6957–6966.

[21] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. 2014. Generative Adversarial Nets. In *Advances in Neural Information Processing Systems*, Z. Ghahramani, M. Welling, C. Cortes, N. Lawrence, and K.Q. Weinberger (Eds.), Vol. 27. Curran Associates, Inc.

[22] Karol Gregor, Ivo Danihelka, Alex Graves, Danilo Rezende, and Daan Wierstra. 2015. DRAW: A Recurrent Neural Network For Image Generation. In *Proceedings of the 32nd International Conference on Machine Learning (Proceedings of Machine Learning Research, Vol. 37)*, Francis Bach and David Blei (Eds.). PMLR, Lille, France, 1462–1471.

[23] Shuyang Gu, Dong Chen, Jianmin Bao, Fang Wen, Bo Zhang, Dongdong Chen, Lu Yuan, and Baining Guo. 2022. Vector Quantized Diffusion Model for Text-to-Image Synthesis. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 10696–10706.

[24] Yaru Hao, Zewen Chi, Li Dong, and Furu Wei. 2022. Optimizing Prompts for Text-to-Image Generation. *arXiv preprint arXiv:2212.09611* (2022).

[25] Sandra G Hart and Lowell E Staveland. 1988. Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. In *Advances in psychology*. Vol. 52. Elsevier, 139–183.

[26] Yi He, Xi Yang, Chia-Ming Chang, Haoran Xie, and Takeo Igarashi. 2023. Efficient Human-in-the-loop System for Guiding DNNs Attention. In *Proceedings of the 28th International Conference on Intelligent User Interfaces (IUI '23)*. Association for Computing Machinery, New York, NY, USA, 294–306. https://doi.org/10.1145/3581641.3584074

[27] Amir Hertz, Ron Mokady, Jay Tenenbaum, Kfir Aberman, Yael Pritch, and Daniel Cohen-Or. 2022. Prompt-to-Prompt Image Editing with Cross Attention Control. *arXiv preprint arXiv:2208.01626* (2022).

[28] Eric Horvitz. 1999. Principles of mixed-initiative user interfaces. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '99)*. Association for Computing Machinery, New York, NY, USA, 159–166. https://doi.org/10.1145/302979.303030

[29] Rubaiat Habib Kazi, Tovi Grossman, Hyunmin Cheong, Ali Hashemi, and George Fitzmaurice. 2017. DreamSketch: Early Stage 3D Design Explorations with Sketching and Generative Design. In *Proceedings of the 30th Annual ACM Symposium on User Interface Software and Technology (UIST '17)*. Association for Computing Machinery, New York, NY, USA, 401–414. https://doi.org/10.1145/3126594.3126662

[30] Amy J Ko, Brad A Myers, and Htet Htet Aung. 2004. Six Learning Barriers in End-User Programming Systems. In *2004 IEEE Symposium on Visual Languages-Human Centric Computing*. IEEE, 199–206.

[31] Hyung-Kwon Ko, Gwanmo Park, Hyeon Jeon, Jaemin Jo, Juho Kim, and Jinwook Seo. 2023. Large-scale Text-to-Image Generation Models for Visual Artists' Creative Works. In *Proceedings of the 28th International Conference on Intelligent User Interfaces (IUI '23)*. Association for Computing Machinery, New York, NY, USA, 919–933. https://doi.org/10.1145/3581641.3584078

[32] Bonan Kou, Shengmai Chen, Zhijie Wang, Lei Ma, and Tianyi Zhang. 2023. Is Model Attention Aligned with Human Attention? An Empirical Study on Large Language Models for Code Generation. *arXiv preprint arXiv:2306.01220* (2023).

[33] Bowen Li, Xiaojuan Qi, Thomas Lukasiewicz, and Philip Torr. 2019. Controllable Text-to-Image Generation. In *Advances in Neural Information Processing Systems*, H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. Fox, and R. Garnett (Eds.), Vol. 32. Curran Associates, Inc.

[34] Q. Vera Liao, Daniel Gruen, and Sarah Miller. 2020. Questioning the AI: Informing Design Practices for Explainable AI User Experiences. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–15. https://doi.org/10.1145/3313831.3376590

[35] Jiachang Liu, Dinghan Shen, Yizhe Zhang, William B Dolan, Lawrence Carin, and Weizhu Chen. 2022. What Makes Good In-Context Examples for GPT-3?. In *Proceedings of Deep Learning Inside Out (DeeLIO 2022): The 3rd Workshop on Knowledge Extraction and Integration for Deep Learning Architectures*. 100–114.

[36] Vivian Liu and Lydia B Chilton. 2022. Design Guidelines for Prompt Engineering Text-to-Image Generative Models. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems (CHI '22)*. Association for Computing Machinery, New York, NY, USA, Article 384, 23 pages. https://doi.org/10.1145/3491102.3501825

[37] Vivian Liu, Han Qiao, and Lydia Chilton. 2022. Opal: Multimodal Image Generation for News Illustration. In *Proceedings of the 35th Annual ACM Symposium on User Interface Software and Technology (UIST '22)*. Association for Computing Machinery, New York, NY, USA, Article 73, 17 pages. https://doi.org/10.1145/3526113.3545621

[38] Vivian Liu, Jo Vermeulen, George Fitzmaurice, and Justin Matejka. 2023. 3DALL-E: Integrating Text-to-Image AI in 3D Design Workflows. In *Proceedings of the 2023 ACM Designing Interactive Systems Conference (DIS '23)*. Association for Computing Machinery, New York, NY, USA, 1955–1977. https://doi.org/10.1145/3563657.3596098

[39] Ryan Louie, Andy Coenen, Cheng Zhi Huang, Michael Terry, and Carrie J. Cai. 2020. Novice-AI Music Co-Creation via AI-Steering Tools for Deep Generative Models. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3313831.3376739

[40] Scott M Lundberg and Su-In Lee. 2017. A Unified Approach to Interpreting Model Predictions. In *Advances in Neural Information Processing Systems*, I. Guyon, U. Von Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett (Eds.), Vol. 30. Curran Associates, Inc. https://proceedings.neurips.cc/paper_files/paper/2017/file/8a20a8621978632d76c43dfd28b67767-Paper.pdf

[41] Elman Mansimov, Emilio Parisotto, Jimmy Lei Ba, and Ruslan Salakhutdinov. 2015. Generating Images from Captions with Attention. *arXiv preprint arXiv:1511.02793* (2015).

[42] J. Marks, B. Andalman, P. A. Beardsley, W. Freeman, S. Gibson, J. Hodgins, T. Kang, B. Mirtich, H. Pfister, W. Ruml, K. Ryall, J. Seims, and S. Shieber. 1997. Design galleries: a general approach to setting parameters for computer graphics and animation. In *Proceedings of the 24th Annual Conference on Computer Graphics and Interactive Techniques (SIGGRAPH '97)*. ACM Press/Addison-Wesley Publishing Co., USA, 389–400. https://doi.org/10.1145/258734.258887

[43] Justin Matejka, Michael Glueck, Erin Bradner, Ali Hashemi, Tovi Grossman, and George Fitzmaurice. 2018. Dream Lens: Exploration and Visualization of Large-Scale Generative Design Datasets. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3173574.3173943

[44] Andrew M Mcnutt, Chenglong Wang, Robert A Deline, and Steven M. Drucker. 2023. On the Design of AI-powered Code Assistants for Notebooks. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 434, 16 pages. https://doi.org/10.1145/3544548.3580940

[45] Jonas Oppenlaender. 2022. A Taxonomy of Prompt Modifiers for Text-To-Image Generation. *arXiv preprint arXiv:2204.13988* 2 (2022).

[46] Nikita Pavlichenko and Dmitry Ustalov. 2023. Best Prompts for Text-to-Image Models and How to Find Them. In *Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR '23)*. Association for Computing Machinery, New York, NY, USA, 2067–2071. https://doi.org/10.1145/3539618.3592000

[47] Fabian Pedregosa, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, Peter Prettenhofer, Ron Weiss, Vincent Dubourg, et al. 2011. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research* 12 (2011), 2825–2830.

[48] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. 2021. Learning Transferable Visual Models From Natural Language Supervision. In *Proceedings of the 38th International Conference on Machine Learning (Proceedings of Machine Learning Research, Vol. 139)*, Marina Meila and Tong Zhang (Eds.). PMLR, 8748–8763.

[49] Aditya Ramesh, Prafulla Dhariwal, Alex Nichol, Casey Chu, and Mark Chen. 2022. Hierarchical Text-Conditional Image Generation with CLIP Latents. *arXiv preprint arXiv:2204.06125* 1, 2 (2022), 3.

[50] Aditya Ramesh, Mikhail Pavlov, Gabriel Goh, Scott Gray, Chelsea Voss, Alec Radford, Mark Chen, and Ilya Sutskever. 2021. Zero-Shot Text-to-Image Generation. In *Proceedings of the 38th International Conference on Machine Learning (Proceedings of Machine Learning Research, Vol. 139)*, Marina Meila and Tong Zhang (Eds.). PMLR, 8821–8831.

[51] Scott Reed, Zeynep Akata, Xinchen Yan, Lajanugen Logeswaran, Bernt Schiele, and Honglak Lee. 2016. Generative Adversarial Text to Image Synthesis. In *Proceedings of The 33rd International Conference on Machine Learning (Proceedings of Machine Learning Research, Vol. 48)*, Maria Florina Balcan and Kilian Q. Weinberger (Eds.). PMLR, New York, New York, USA, 1060–1069.

[52] Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. 2016. "Why Should I Trust You?": Explaining the Predictions of Any Classifier. In *Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining (KDD '16)*. Association for Computing Machinery, New York, NY, USA, 1135–1144. https://doi.org/10.1145/2939672.2939778

[53] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. 2022. High-Resolution Image Synthesis with Latent Diffusion Models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 10684–10695.

[54] Christoph Schuhmann, Romain Beaumont, Richard Vencu, Cade Gordon, Ross Wightman, Mehdi Cherti, Theo Coombes, Aarush Katta, Clayton Mullis, Mitchell Wortsman, et al. 2022. Laion-5b: An open large-scale dataset for training next generation image-text models. 35 (2022), 25278–25294.

[55] Taylor Shin, Yasaman Razeghi, Robert L Logan IV, Eric Wallace, and Sameer Singh. 2020. AutoPrompt: Eliciting Knowledge from Language Models with Automatically Generated Prompts. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. Association for Computational Linguistics, Online, 4222–4235. https://doi.org/10.18653/v1/2020.emnlp-main.346

[56] Ben Shneiderman. 1981. Direct Manipulation: A Step Beyond Programming Languages. In *Proceedings of the Joint Conference on Easier and More Productive Use of Computer Systems.(Part-II): Human Interface and the User Interface-Volume 1981*. 143.

[57] Ben Shneiderman. 1982. The future of interactive systems and the emergence of direct manipulation. *Behaviour & Information Technology* 1, 3 (1982), 237–256.

[58] Hendrik Strobelt, Albert Webson, Victor Sanh, Benjamin Hoover, Johanna Beyer, Hanspeter Pfister, and Alexander M Rush. 2022. Interactive and Visual Prompt Engineering for Ad-hoc Task Adaptation with Large Language Models. *IEEE Transactions on Visualization and Computer Graphics* 29, 1 (2022), 1146–1156.

[59] Raphael Tang, Linqing Liu, Akshat Pandey, Zhiying Jiang, Gefei Yang, Karun Kumar, Pontus Stenetorp, Jimmy Lin, and Ferhan Ture. 2023. What the DAAM: Interpreting Stable Diffusion Using Cross Attention. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. Association for Computational Linguistics, 5644–5659.

[60] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin. 2017. Attention is All you Need. In *Advances in Neural Information Processing Systems*, I. Guyon, U. Von Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett (Eds.), Vol. 30. Curran Associates, Inc.

[61] Dakuo Wang, Justin D. Weisz, Michael Muller, Parikshit Ram, Werner Geyer, Casey Dugan, Yla Tausczik, Horst Samulowitz, and Alexander Gray. 2019. Human-AI Collaboration in Data Science: Exploring Data Scientists' Perceptions of Automated AI. *Proc. ACM Hum.-Comput. Interact.* 3, CSCW, Article 211 (nov 2019), 24 pages. https://doi.org/10.1145/3359313

[62] Pichao Wang, Xue Wang, Fan Wang, Ming Lin, Shuning Chang, Hao Li, and Rong Jin. 2022. KVT: k-NN Attention for Boosting Vision Transformers. In *European Conference on Computer Vision*. Springer, 285–302.

[63] Qing Wang, Jiaming Zhang, Kailun Yang, Kunyu Peng, and Rainer Stiefelhagen. 2022. MatchFormer: Interleaving Attention in Transformers for Feature Matching. In *Proceedings of the Asian Conference on Computer Vision (ACCV)*. 2746–2762.

[64] Sitong Wang, Savvas Petridis, Taeahn Kwon, Xiaojuan Ma, and Lydia B Chilton. 2023. PopBlends: Strategies for Conceptual Blending with Large Language Models. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 435, 19 pages. https://doi.org/10.1145/3544548.3580948

[65] Yunlong Wang, Shuyuan Shen, and Brian Y Lim. 2023. RePrompt: Automatic Prompt Editing to Refine AI-Generative Art Towards Precise Expressions. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 22,

29 pages.   https://doi.org/10.1145/3544548.3581402

[66] Zhou Wang, Alan C Bovik, Hamid R Sheikh, and Eero P Simoncelli. 2004. Image quality assessment: from error visibility to structural similarity. *IEEE Transactions on Image Processing* 13, 4 (2004), 600–612.

[67] Zijie J Wang, Evan Montoya, David Munechika, Haoyang Yang, Benjamin Hoover, and Duen Horng Chau. 2023. DiffusionDB: A Large-scale Prompt Gallery Dataset for Text-to-Image Generative Models. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. Association for Computational Linguistics, 893–911.

[68] Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. 2022. Chain-of-Thought Prompting Elicits Reasoning in Large Language Models. 35 (2022), 24824–24837.

[69] Justin D Weisz, Michael Muller, Jessica He, and Stephanie Houde. 2023. Toward General Design Principles for Generative AI Applications. *arXiv preprint arXiv:2301.05578* (2023).

[70] Yuxin Wen, Neel Jain, John Kirchenbauer, Micah Goldblum, Jonas Geiping, and Tom Goldstein. 2023. Hard Prompts Made Easy: Gradient-Based Discrete Optimization for Prompt Tuning and Discovery. *arXiv preprint arXiv:2302.03668* (2023).

[71] Chenfei Wu, Jian Liang, Lei Ji, Fan Yang, Yuejian Fang, Daxin Jiang, and Nan Duan. 2022. Visual Synthesis Pre-training for Neural visUal World creAtion. In *European Conference on Computer Vision*. Springer Nature Switzerland, Cham, 720–736.

[72] Tongshuang Wu, Michael Terry, and Carrie Jun Cai. 2022. AI Chains: Transparent and Controllable Human-AI Interaction by Chaining Large Language Model Prompts. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems (CHI '22)*. Association for Computing Machinery, New York, NY, USA, Article 385, 22 pages.   https://doi.org/10.1145/3491102.3517582

[73] Chuan Yan, John Joon Young Chung, Yoon Kiheon, Yotam Gingold, Eytan Adar, and Sungsoo Ray Hong. 2022. FlatMagic: Improving Flat Colorization through AI-driven Design for Digital Comic Professionals. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems (CHI '22)*. Association for Computing Machinery, New York, NY, USA, Article 380, 17 pages.   https://doi.org/10.1145/3491102.3502075

[74] Shunyu Yao, Dian Yu, Jeffrey Zhao, Izhak Shafran, Thomas L Griffiths, Yuan Cao, and Karthik Narasimhan. 2023. Tree of Thoughts: Deliberate Problem Solving with Large Language Models. In *Thirty-seventh Conference on Neural Information Processing Systems*.

[75] Mehmet Ersin Yumer, Siddhartha Chaudhuri, Jessica K. Hodgins, and Levent Burak Kara. 2015. Semantic shape editing using deformation handles. *ACM Trans. Graph.* 34, 4, Article 86 (jul 2015), 12 pages.   https://doi.org/10.1145/2766908

[76] Loutfouz Zaman, Wolfgang Stuerzlinger, Christian Neugebauer, Rob Woodbury, Maher Elkhaldi, Naghmi Shireen, and Michael Terry. 2015. GEM-NI: A System for Creating and Managing Alternatives In Generative Design. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems (CHI '15)*. Association for Computing Machinery, New York, NY, USA, 1201–1210. https://doi.org/10.1145/2702123.2702398

[77] JD Zamfirescu-Pereira, Richmond Y Wong, Bjoern Hartmann, and Qian Yang. 2023. Why Johnny Can't Prompt: How Non-AI Experts Try (and Fail) to Design LLM Prompts. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 437, 21 pages.   https://doi.org/10.1145/3544548.3581388

[78] Han Zhang, Tao Xu, Hongsheng Li, Shaoting Zhang, Xiaogang Wang, Xiaolei Huang, and Dimitris N Metaxas. 2017. StackGAN: Text to Photo-realistic Image Synthesis with Stacked Generative Adversarial Networks. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*. 5907–5915.

[79] Zihao Zhao, Eric Wallace, Shi Feng, Dan Klein, and Sameer Singh. 2021. Calibrate Before Use: Improving Few-Shot Performance of Language Models. In *Proceedings of the 38th International Conference on Machine Learning (Proceedings of Machine Learning Research, Vol. 139)*, Marina Meila and Tong Zhang (Eds.). PMLR, 12697–12706.

A STUDY 1: CLOSE-ENDED TASKS

A.1 Task Description

Table A1: Close-ended User Study Tasks

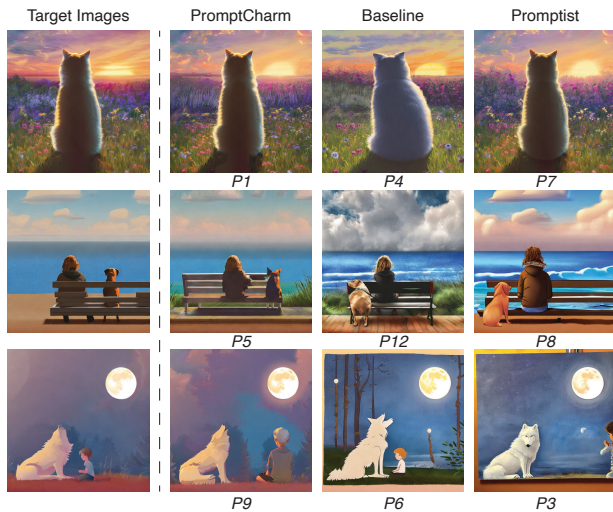| #	Task 1	Task 2	Task 3
Target Image			
Initial Prompt	A painting from behind of an orange cat standing in a field of flowers and watching the sunset.	An image of a girl and her dog sitting on a bench and looking at the sea.	A painting of a wolf sitting next to a human child in front of the full moon.

A.2 Examples of User-created Images

Figure A1: Examples of user-created images in Study 1

B STUDY 2: OPEN-ENDED TASKS

B.1 Task Description

Table B2: Open-ended User Study Tasks

#	Image Subject(s)	Image Scene
Task 1	A dog and a cat	The dog is playing with the cat
Task 2	A group of Canada geese	The geese are walking on a street
Task 3	A penguin	The penguin is playing in the snow

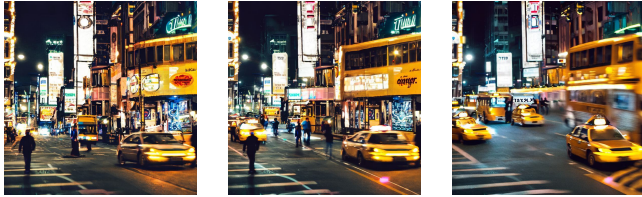## B.2 Examples of User-created Images

Figure B2: Examples of user-created images in Study 2

C MODEL ATTENTION ADJUSTMENT

Example 1 prompt:

a clear image of a bustling city street at night, featuring a [taxi], a bus, neon signs, and people walking.

(a) 0.5x attention score to [taxi]

(b) No adjustment.

(c) 2x attention score to [taxi]

Figure C3: Adjusting model attention to the word [taxi].

Example 2 prompt:

a clear image of a cozy library room with a fireplace, comfortable armchairs, shelves filled with books, and a large window showing a [snowy] landscape outside.

(a) 0.5x attention score to [snowy]

(b) No adjustment.

(c) 2x attention score to [snowy]

Figure C4: Adjusting model attention to the word [snowy].

Example 3 prompt:

an oil painting of a desert scene with cacti, under a heavy [rain], where each raindrop is distinctly visible.

(a) 0.5x attention score to [rain]

(b) No adjustment.

(c) 2x attention score to [rain]

Figure C5: Adjusting model attention to the word [rain].

Example 4 prompt:

a painting of a lion, a [giraffe], a parrot, and a dolphin.

(a) 0.5x attention score to [giraffe]

(b) No adjustment.

(c) 2x attention score to [giraffe]

Figure C6: Adjusting model attention to the word [giraffe].