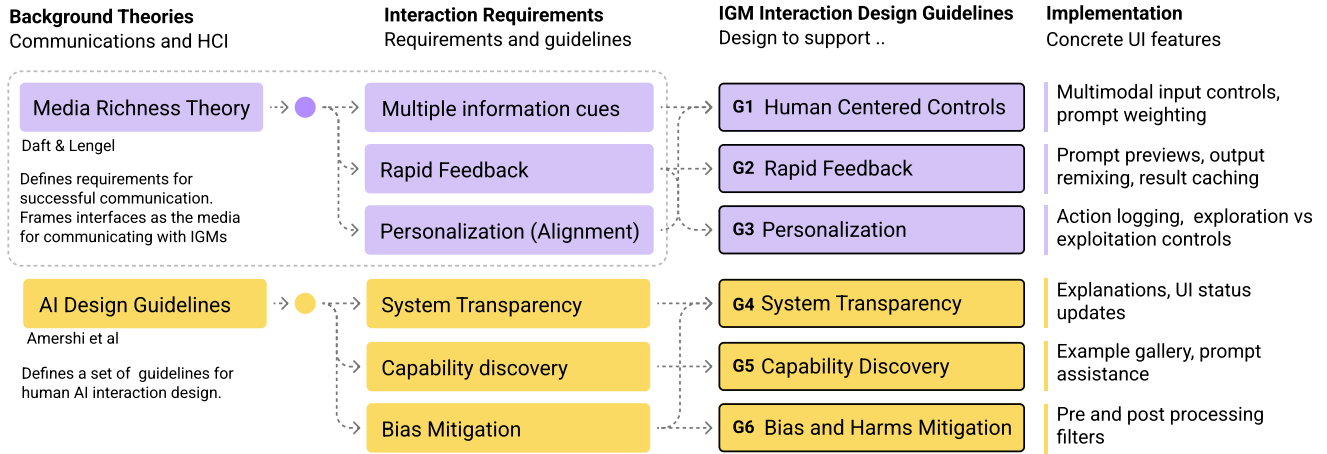# [Draft]Interaction Design for Systems that Integrate Image Generation Models

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Figure 1: In this work we draw on communication theory (media richness theory [3]) and research on Human-AI interaction design [1] in defining a set of interaction guidelines for systems that integrate image generation models (IGMs). We demonstrate these guidelines concretely as features within *Peacasso* - that allows users to generate images using IGMs.

ABSTRACT

Recent advances in multimodal image generation models (**IGM**s) have enabled the creation of high quality images on *consumer compute devices*. As developers integrate these models into new creative applications, it is still unclear how best to design experiences that *align* the vast technical capabilities of these models with end user goals. This work addresses this *alignment/control* problem in two ways. First, we draw on theories from communications (media richness theory) and Human-AI interactions in deriving a set of high level guidelines for building **IGM**s - designing for *human centered controls*, *rapid feedback*, *personalization*, *transparency*, *capability discovery* and *harms mitigation*. Next, we present *Peacasso* - an open source user interface that implements these guidelines, with features including an image generation editor (text/image prompting, inpainting, outpainting), process curator, control mechanisms (prompt remixing, latent space navigation) and sense making tools (prompt preview, explanations, latent space explore). We demonstrate the utility of the *Peacasso* api in building

novel user interactions by implementing a set of high level application use cases (e.g., presets for tiling, video generation and story generation). *Peacasso* is available on Github.

1 INTRODUCTION

The ability to convert natural language text to high quality images that capture concepts expressed in the text has been the focus of multiple computer vision research streams over the last decade. Systems that integrate these capabilities have potential to improve the *image creation* user experience by converting a difficult task (e.g., illustrating images is high cognitive load and high effort) into a simple task (e.g., describing an image in natural language is low

cognitive load, low effort). Recent advances in text-to-image generation models, specifically diffusion models such as DALLE-2 [12], Stable Diffusion [13], Midjourney [17] have shown particularly compelling results - they generate high quality images, at high resolution, on consumer compute devices purely from text. In essence, these advances inspired the proliferation of new tools and systems where an AI model works in concert with a human in co-creating visual imagery. There have now been plugins that integrate **IGM**s into existing design tools like Adobe Photoshop[18] as well as brand new tools such as Dream Studio[1] etc.

Within these applications, a human provides some representation of the goal of the collaboration (typically via some input mechanism such as text or other modalities, see section 2.2), and the AI model produces visual imagery *guided* by this input. Achieving these goals typically involves the creation of some *system* - an interface that mediates communication between the *human*, and the **IGM** *model* - towards achieve a set of goals for the human. Note that the *interface* may implement additional integrations with a set of *external entities* as needed. A systems perspective is valuable, important given that the interface component plays a profound role in shaping the socio-technical outcomes of HumanAI collaboration *beyond* the core technical capabilities of the underlying model. For example, pairing an **IGM** with frame curation and text curation tools and genreation pipleine can lead to the generation of videos or illustrated books; pairing an interface with appropriate capabilty discovery mechanisms can reduce time to productivity or quality of output.

In practice, developing systems that integrate **IGM**and enable *Co − Creation* faces a few challenges. Specifically the probablistic nature of machine learning models make them unpredictable when used as design materials, which can result in disruptive, confusing or harmful experiences [1]. Furthermore, while the underlying models are highly capable (i.e., can generate complex, novel imagery), a significant effort is still required of the user to craft the right input (e.g., a text prompt) that steers the model towards a desired output. Specifically, current input modalities (text, image) by themselves do not offer sufficient precision/control to the user in navigating the complex latent knowledge space learned by **IGM**s. Finally, progress in interating on interaction design affordances with **IGM**s is currently limited by the lack of development, design or research focused tools and api's for **IGM**s. In this work, we argue that these challenges can be addressed to some extent by improving the interaction interface through which humans interact with the underlying models (towards the goal of aligning user value with model capabilities).

Overall the contributions of this work are summarized as follows:

- We derive a set of 6 high level design guidelines for building **IGM** interfaces - designing for *human centered controls*, *rapid feedback*, *personalization*, *transparency*, *capability discovery* and *harms mitigation.*. These guidelines are informed by existing theory - we adapt insights from media richness theory [3] that highlights requirements for effective communication - and adapt guidelines for human-ai interaction [1].

- We contribute Peacasso - a library (backend api and user interface) for interacting with **IGM**s. It implements a generic image

generation editor (text/image prompting, inpainting, outpainting) and a set of new UI intetrventions that operationalize the guidelines proposed. These include process and outcome curation model, sense making tools (prompt preview and explanations) and a set of high level application presets (tiling, video generation, story generation). While *Peacasso* provides a UI interface (see Figure 3), it also provides the first flexible backend api designed to enable research and experimentation on novel interfaces for **IGM**s. We validate the utility of *Peacasso*'s api via several illustrative usecases.

2 RELATED WORK

Systems that integrate **IGM**s consist of multiple components - image generation models, a core user interface and third party dependencies. These components in turn are informed by advances in core image generation algorithms, the introduction of multiple input modalities that control generation and a burgeoning community of practice that have concurrency shaped the field.

2.1 Image Generation Models

The ability to generate high quality novel images has been the target of extensive research in the deep learning and computer vision field. Generative adversarial networks (GANs) showed us that we could implicitly learn the distribution of data and draw samples from this distribution; VAEs showed us how to explicitly map data to a (gaussian) distribution and learn the parameters of this distribution. However, we could only generate small blurry images - 64x64px; and when we got better at larger images, we still had diversity and quality problems and at very high computational cost. While these models enabled free form generation of novel images, the inference setup offered little control (random noise vector used as a latent code used to sample from the learned distribution in generating an image). To advance on this, researchers explored the use of conditional generation, where discrete labels corresponding to dimensions were associated with the training process and used during inference to control generations along these dimensions Engel et al. [4], Radford et al. [11].

Recently, there has been the introduction of diffusion models - models that learn a noising process (adding noise to some input across several steps until that input is indistinguishable from pure noise) and a denoising process that reverses the noising process (removes noise across several steps until a legit image is recovered). The name diffusion comes from a branch of physics (nonequilibrium thermodynamics) which describes how particles may move from areas of high concentration to lower concentration in order to achieve equilibrium. Examples include DALLE [12], GLIDE [8], DALLE-2 [12], IMAGEN [14]. In practice, while diffusion models yield very high image quality, many challenges (slow sampling due to a large number of denoising steps etc) have had to be addressed to make this process usable in image generation - with landmark papers like , DDPM [5], DDIM [15] etc.

More recently latent diffusion models [13] were introduced and address an important challenge with diffusion models - their memory requirements. They achieve this by proposing we apply the noising and denoising process in latent space (instead of raw image/pixel space) and then map this latent space back to the image

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[1]Dream Studio https://beta.dreamstudio.ai/dream

Table 1: Input modalities provided by image generation models can be categorized in terms of the control precision that they provide to the user and the ease with which humans can author or interpret those modalities (human intelligibility).

Atomic Input Modality	Derivative Modality	Description	Precision	Human Intelligibility
Latent Code	Random seed	Seed used to generate latent code	low	low
	Latent Code	Latent code used to sample latent space	low	low
Text	Text category	Class name for class conditioned generation	medium	high
	Natural language	Natural language descriptions used to guide image generation model	medium	high
	Prompt natural language	Natural language specific to prompting syntax	high	medium
	Weighted prompt natural language	Applying weighted combinations of text descriptions	high	high
Image	Image	Initializing latent code from image	high	high
	Text + Image	Natural language guidance + image control	high	high
	Text + Image + mask	Text + image constrained to a region in the input image	high	high

space. This dramatically reduces the memory requirements for running diffusion models, hence the competitive results we have seen recently on consumer GPUs. Finally, these models address the issue of control by leveraging advances from large multimodal (text+image models e.g. CLIP Radford et al. [11]) where generation is conditioned on free form text representation from these multimodal models.

2.2 Control Modalities for Image Generation Models

To facilitate the generation of arbitrary images, **IGM**'s must learn an efficient latent representation that covers the dataset on which they are trained. The resulting $latent representation$ is treated as a distribution that can be sampled from using a $noise vector$ or $latent code$. In practice, the degree to which this learned representation (aka latent space) can be navigated or **controlled** is directly correlated with their usefulness [10]. In this section, we outline a core set of $atomic$ control input types to an **IGM** and their derivatives (latent code, text, image - see 1). For each of these modalities, we discuss their implications for control precision - *how much control the user has over the generated image* and human intelligibility - *the ease with which a human can author and make sense of meaningful versions of the input.*

- **Latent Code**. This line of research explores methods for manipulating some *existing* latent code that results in predictable outcomes. For example, learning operations on $latent code$ for a generated image that might interpolate features associated with images in human datasets such as like age, gender [6] or dataset invariant attributes such as scale and translation Plumerault et al. [10]. Note that the initial latent code is typically based on some random seed (used to sample the learned distribution), which itself is not directly interpretable.
- **Text Input**. This approach involves guiding the generation image generation using representations learned from text. For example, diffusion models may start with some arbitrary random noise vector based on a *seed*, and iteratively refine the generated image in a manner that is conditioned on text represenation from a multimodal modal. While this approach provides user agency to describe a scene in natural language sentences, there is limited control Text is by definition underspecied, it the information contained in 5 or 50 words must be converted into an image .. a scene that can be represented in 1,000 words. Furthermore, while these models do support natural language, effective prompts that generate high quality images have been shown to be *less natural*,

often requiring the use of specialized modifier keywords, art styles and descriptors that vary with model and training dataset.
- **Image Input** : In this regime, images are provides as input to the model. In the case of diffusion models, $latent code$ is derived based on the input image and used as the starting point for the diffusion process. Derivatives of this atomic input modality include the use of conditional signals [13, 19] such as (i) Masking: parts of the input image may be masked and the model is tasked with completing a region corresponding to the mask (inpainting). (ii) Depth Maps (iii) Edge Maps. (iv) Keypoints. (v) Segmentation Maps .

These control modalities can also be classified in terms of human intelligibility (the ease with which a human an author control artifacts) and control precision (the level of control that an mechanism offers over the generated image). For example, a simple random latent code lets the user generate a random image, the only guarantee being that the image conforms to properties of the dataset from which the model was trained. On the other hand natural language allows the user to describe salient concepts that are in turn represented in the generated image. On the other hand image input paired with text description provides control on concepts in the image and opportunity to improve specific sections of the image (in painting).

In this work, we explore how input modalitied offered by **IGM** s map to design decisions and resulting guidelines.

2.3 Community Practices on Image Generation Systems

Machine learning is a rapidly evolving field where community engineering and experimentation remains a key driver of progress. We see a similar trend in the **IGM** field where there has been a proliferation of community **IGM**'s tools. For context, the first latent diffusion model weights [13] that allowed generation of images on consumer compute was releasd in August 16, 2022. In the following 3 months (up until November 15, 2022), there over over 300 github repositories that have the $stable-diffusion$ topic tag. Early repositories provided scripts and notebooks that showed examples of how to load the model and run basic predictions. The next wave explored more complex parameterization of the model for imporove control (e.g., specifying denoising steps, image size, seed resizing, use of negative prompts etc etc). There were also efforts to improve the base models (model finetuning like textual inversion, dream booth), chaining multiple models for improved results (e.g., using ESRGAN for improved resolution, fixing faces and hands), prompt

support tools (e.g., generating example prompts from images) and formalization/taxonomies of techniques for efficient prompt engineering [7, 9]. Next there were examples that sought to explore more complex application areas (e.g., video generation via interpolation over infinite landscapes). More recent efforts have also begun to explore full fledged user interfaces beyond notebooks and scripts e.g., UIs bundled as web services, applications runing locally on MacOS/windows/linux and mobile. This work inherits insights from the community of practice. Specifically, *Peacasso* takes a UI first approach, implements control mechanisms, explores application presets but also presents *new UI capabilities* including control mechanisms (e.g., prompt mixing), explanations (prompt previews, prompt token examples), prompt suggestions, and latent space path construction.

3 INTERACTION DESIGN: REQUIREMENTS AND GUIDELINES

Existing studies have explored requirements for good interaction across multiple parties. In this section, we focus on two of these studies. First we explore interaction requirements for human-human communication [3]. Second, we explore interaction requirements for human-AI interaction [1]. We then use these insights to derive a set of high level design guidelines for systems that integrate **IGM** models.

3.1 Requirements for Effective Communication: A Media Richness Theory Perspective

in 1986, Daft and Lengel [3] began studying drivers for *effective communication* media within organizations. Their work, known today as media richness theory describe rich media as one that fosters understanding, learning and minimizes ambiguity or uncertainty [3]. They argue that media richness is a function of several characteristics including - ability to handle multiple information cues simultaneously - ability to facilitate rapid feedback, ability to establish a personal focus, ability to utilize natural language, minimize uncertainty (examples, capability discovery). In turn, rich media drives *effective communication* by reducing uncertainty especially when processing equivocal information (information that may be subject to multiple interpretations). This observation is especially important in the context of **IGM** systems where the output of the model is subject to multiple interpretations e.g., a prompt can result in **multiple valid images**. While *media richness theory* aims to explain information processing behaviors between humans (or organizations), it can be applied in framing communication challenges that arise when humans work with **IGM** systems. Specifically, we frame the **IGM** interface as a communication medium and argue that richness of the interface directly impacts the effectiveness of the collaboration between human and AI. By revisiting the characteristics of rich media, we can derive a set of interaction requirements for **IGM** systems.

3.1.1 Ability to Handle Multiple Information Cues Simultaneously. Daft and Lengel [3] give cite face-to-face communication as rich media given the they offer a party the ability to integrate multiple cues such as body language, tone of voice, personal contact, and convey messages in *natural language.* Similarly, an **IGM** interface

should strive towards providing multiple rich modalities that are human-intelligible and easy to author such as natural language text, images, audio and video(see table 1 on intelligbility of model input affordances).

> **Guideline 1: Human Centered Control**
>
> (1) Support creation of multiple input modalities that are *human-intelligible* and *human-authorable* such as natural language text, images, audio.
> (2) Efficiently **_map_** human-intelligible and human-authorable input mechanisms (e.g., natural language, images, audio which may offer low levels of precision in fully specifying intent) to machine intelligible input (e.g., a latent code, text embedding, seed etc, that offers high precision in navigating model's latent space).
> (3) Support the *combination* of multiple modalities towards improving human agency and fine grained control of results.

3.1.2 Ability to Facilitate Rapid Feedback. Daft and Lengel [3] argue that rich media facilitate rapid feedback by allowing for immediate feedback and response; in turn, this allows users to converge on a common interpretation. Similarly, an **IGM** should offer affordances for rapid, timely feedback and iteration on ideas. This is especially important for design with **IGM**'s where each generation may take some time and often requires costly GPU compute. For example, a user should be able to compare results, select results of interest, make edits, request new results or interupt the model as needed.

> **Guideline 2: Rapid Feedback**
>
> (1) Support a *iterative creative* process composed of *actions* where the output of each *actions* may be used as input for other actions.
> (2) Support methods that help the user make sense of how their input choices may impact the output of the model with minimal resources (time and compute).

3.1.3 Ability to Establish a Personal Focus. Finally, Daft and Lengel [3] find that communications that were personalized and focused on the individual were more effective. Similarly, an **IGM** interface should support fine grained control in representing their preferences and intent. For example, providing methods specifying a variety of concepts or styles to be represented in the result can enhance level of control av'ailable to the user. Also, a good **IGM** interface should support users as they switch between various mental models.

Users can have one of two distinct high level mental models and associated goals as they interact **IGM**systems. This categorization of user behaviour is not novel and has been mirrored on multiple creativity or search tools [].

Understanding these mental models can help in understanding the underlying user goals and informing the appropriate set of interaction affordances (workflows) that can be offered to users.

- **Exploratory Mental Model** In the exploratory mindset, the user comes to to tool with a limited understanding of the exact tasks. First, they
limited information and expertise - they may not know the exact outcome they wish to accomplish, may be limited in artistic skill, limited in the capabilities of the model. Despite all of this, their goal is to engage in the creative process ..extract high quality imagery that allows th particularly have a clear idea of their goals,
- **Exploitative Mental Model**
In this model, users have a clear idea of what they are interested in creating. The bulk of their effort is geared towards representing their intent using the ineterface provided by the system such that their goal is achieved.

Guideline 3: Personalization

- -

(1) Support multiple mental models based on the user's needs (e.g.,)exploration and exploitation .
(2) Support low level exploration as well as high level application workflow presets.

3.2 Guidelines for Human AI Interaction

While an MRT lens allows us to identify communication requirements for an **IGM**system, one limitation is that it assume human-human communication, hence a need to account for human-ai communication requirements. To address this, we turn to insights from research on design guidelines for human ai interaction by Amershi et al. [1]. Amershi et al. [1] acknowledge that results from AI models are performed under uncertainty leading to unpredictable outcomes that may be disruptive, offensive or unsafe. provide a set of interaction guidelines that underpin scenarios where humans interact with AI models. In this section we revisit a subset of those guidelines contextualized to the image generation scenario.

To enable cocreation, the user must understand the core capabilities of tan AI model and be appropriately trained on how to elicit those capabilities. For example, it is usefulf for the user to understand that the model's behaviour is restricted to the knowledge within the trainig dataset. Interaction breaks down when the user demands when the user is not aware of the limiations of the model and attempts to requests tasks beyond the model's ability or consistently under utilizes the model.

[7] propose guidelines for creating prompts that are effective in eliciting desired results from AI models. They recommend steps like mutliple generations to help users build a mental model of model behavior, the need for rapid iteration, need for diverse style exploration and need for warnings of potentially offensive content.

Guideline 4: Transparency

- -

(1) Provide tools that help the user make sense of the model's capabilities and limitations.

Guideline 5: Capability Discovery

- -

(1) Support controls that help the user discover and understand the capabilities of the model.

Guideline 6: Bias and Harm Mitigation

- -

(1) Support controls that minimize the risk of results that reinforce bias or harm.

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4 PEACASSO

In this section we discuss the design and technical implementation of *Peacasso* - a tool and user interface to support experimentation with **IGM**s. *Peacasso*implements concrete features informed by the design guidelines discussed in section 3 (see Fig 1). It consists of the following components: - a set of ***core modules***, a ***web api*** and a front end ***user interface*** as shown in Figure 2 .

4.1 Core Modules

Core modules focus on implementing interfaces for querying the underlying stable diffusion model. This includes a unified image generator pipeline for generating images, and an applications helper module for implementing high level application presets.

4.1.1 (Unified) Image Generator Pipeline. This module implements a single unified image generation pipeline that is parameterized and exposes all model functionality - text to image, image to image, mask+image to image ie. inpainting. This design approach is memory friendly as only a single version of each model component is loaded and reused as needed. Input signature to this module is defined by a *GeneratorConfig* data model which is shared across the backend api and the front end interface as the primary signature for generating images.

4.1.2 Applications Runner. This module implements several application workflows that may call the unified image generation pipeline on demand (or process its outputs) in addressing specific application workflows. For example, a tiling application workflow may take a *PromptConfiguration* as input or an image, recompose a call to the generation pipeline .

4.1.3 Prompt Helper. This module implements a set of functions to support the user in crafting prompts used for generation. It currently includes a prompt predictor model trained on example stable diffusion prompts.
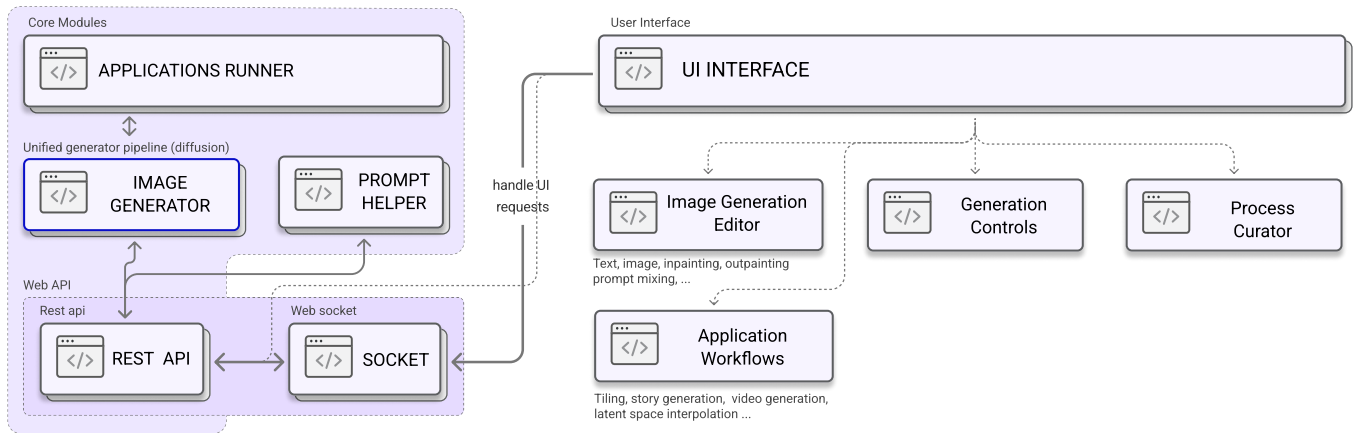
Figure 2: Architecture diagram for the *Peacasso* library.

4.2 Web API

Peacasso provides a backend web api built with Fastapi. Two server end points are provided: (a) a rest based service endpoint that calls the core modules. This endpoint is decoupled from other services to allow the service run on a dedicated server that can be provisioned, scaled and managed independently. (b) A web socket based service endpoint that provides a real time interface for interacting with the rest api service. This endpoint is used by the front end to provide a real time interface.

The user interface is built with React (ant design and tailwind css) and provides a UI interface for interacting with the backend.

4.2.1 Generator Controls. A set of controls to configure the generation pipeline and request images from the backend. All of the controls are parameterized by the *GeneratorConfig* data model.

4.3 User Interface: Editor

Provides a set of tools for finegrained control over the prompt used for generation. This includes standard interfaces for editing text, image and mask prompts.

*4.3.1 **Remixing**.* The Editor supports **remixing** where each generated image can be reused as a prompt.

*4.3.2 **Prompt Mixing**.* Sliders for weighted prompt combination where weights are assigned to multiple prompts

*4.3.3 **Latent Code/Seed Exploration**.* All generations require a random seed which is set by the user (an arbitrary integer) or automatically generated. While this number is typically used to ensure reproducibility of results, it can have a significant impact on the generated image. It is also not interpretable and users cannot tell how a small or large seed may lead to different images with all other properties held constant. The seed explanation interface offers a view to help the user make sense of a space of images that correspond to interpolated latent codes based on a range of seeds.

*4.3.4 **Prompt explanation**.* Provides a list of words or a word tree related to each token in the provided prompt. This capability serves to illustrate how the CLIPText model assigns context to the

words in the prompt (e.g. does it see the word glass in terms of a material or in terms of it being a lens.)

*4.3.5 **Prompt suggestion**.* Suggests completions to prompts based on predictions from the prompt helper core module. It provides a UI for visualizing potential completeions and selecting the best one.

*4.3.6 **Latent Space Interpolation (Seed, Image, Prompt)**.* In many cases, it may be useful to explore pathways between multiple positions in the latent space. These positions can be influenced latent code used to sample from the model or the text embedding used to guide generation. *Peacasso* supports an interface that maps human authorable input to model input (G1: 3.1.1) (seed, input image -> latent code, prompt -> text embedding) and generates interpolations between specified locations.

*4.3.7 **Prompt previews**.* For a given prompt, provide a preview of images that are likely to be generated by those prompts. For users unfamiliar with prompt writing or prompt engineering, identifying the right keywords, modeling the impact of word choice on generated image quality can be challenging. To address this, the prompt previews feature works as follows: given a *prompt*, the user is presented with a gallery of images (as well as associated prompts and full model parameters such as seed, cfg, etc) that are likely to be generated by that *prompt*. The current implementation of the feature relies on the lexica.art api which returns results based on embedding similarity (CLIPText) between the provided query and the 5 million human curated generations in the lexica.art database.

This provides some early feedback and capability discovery abilities to the user (G2: 3.1.2 , G5: 3.2). In addition to This can provide rapid feedback in exploring multiple prompts before incure costs associated with new generations (cpu based search vs gpu based generation).

*4.3.8 **Scratchpad**.* A staging area for the user to temporary dock images that are of interest during a sessions. Scratchpad can then be references as an input source for further generation.

*4.3.9 **Gallery/Session Curator**.* This feature enables the user to start a session which records a series of **actions**. Actions may be

generation requests or application workflow requests. A session must be explicitly started and may be automatically stopped based on some time constraints. Session logs can then be saved to a gallery. This provides a shareable log for both their process and outcomes for a given session with benefits in reproducibility of results.

*4.3.10 **Presets**.* Implements presets for a set of applications that may involve image generation. This includes presets for generating tiled images, automated outpainting, video generation, latent space exploration and more.

USE CASES

In this section, we review how two primary personas may adopt peacasso in their workflow - John a researcher and Jane a creative.

Section in progress.

5 FUTURE WORK

5.1 Opportunities in Improving Control

While this work has looked at interface design features that allow the user control the generated output of the model, these approaches may ultimately be limited by the model's capabilities or complexity of UI steps needed to exert control. To address this, there may be other avenues to explore such as:

5.1.1 Prompt Sensitive Training. Perhaps some approach to structuring training data where a model must learn to function at best effort where text was small and text was large. Also, traning paradigms that improve sentitivity to salient words may improve cotnrol. For example, crafting datasets for descriptions with high syntax overlap but low conceptual overlap are equally represented can enalbe the model learn the improtance of salient tokens and reflect ths in generation.

5.1.2 Domain/Style Specific Models. While the current state of the art models are trained on a wide variety of domains, there may be value in training models on a specific domain or style. By constraining a model to a specific style, the burden of control and space for uncertainty is reduced. For example, a model trained on a specific style of art may be able to generate images that are more consistent with the style.

5.2 Image Quality Evaluation

Do authors have the ability to evaluate the quality of the images they generate? Hisotrically, artistic style are a particular skill/craft that is honed over time, leaving the human in a position where they assess a test for which they are neither skilled nor versed.

5.3 Capturing Context to Improve Control: Future Interfaces

An important goal of an **IGM** interface is to efficiently and precisely map the user's intent (as expressed through human-intelligible and human-authorable input modalities like natural language, images, speech/audio, video etc) to the model's capabilities (see guideline G1 `G1: 3.1.1` on human centered control). In many cases, given the vast complexity of the model's latent space, these input modalities may still be insufficient in terms of precision e.g., "a beautiful house

on a hill" could map to many different images. Like many other machine learning problems, the ability of a system to understand and model user context can be leveraged in infering user's intent resulting in better queries on the model's latent space. This may include historical context (e.g., the user's previous interactions with the model), contextual information (e.g., the user's location, time of day, etc) and other personal information (e.g., the user's mood, the user's current task, open applications or tabs, recently authored textetc). In addition, advances in brain computer interfaces (BCI) can be leveraged to explore direct mappings of the user's mental state (thought) to location or samples in the model's latent space. Early examples in this space include work by Chen et al. [2] where they first learn a self-supervised representation of fMRI data and then use this representation reconstruct highly plausible images with semantically matching details from brain recordings using latent diffusion models with double-conditioning. Similarly [16] also propose a method based on a diffusion model (DM) to reconstruct images from human brain activity obtained via functional magnetic resonance imaging (fMRI)

6 LIMITATIONS

This work adopts a theory inspired approach to understanding requirements for **IGM** systems, followed by prototyping a tool that realizes these requirements as demonstrated within illustrative use cases. While these approaches are illuminating, we acknowledge that there are other methods that could further our understanding of **IGM** tool design. For example, we could have conducted a user studies to that evaluate the impact of the prototyped features on task performance. However, we believe that the approach we have taken is a good starting point for future work in this area. Covering all possible theories that could inform the design of **IGM** systems is infeasible; this work explores a communications theory lens (media richness theory [3]) and insights from interaction design (guidelines for human-ai interaction [1]). We believe other theoretical framings will be complementary and valuable in improving our understanding of opportunities in building **IGM** systems.

7 CONCLUSION

In this work, we leveraged insights from established research in communication theory (meida richness theory [3]) and interaction design (guidelines for human-ai interaction [1]) in deriving a set of high level design guidelines for systems that integrate image generation models. To provide a concrete realization of these guidelines, we contribute *Peacasso-* an open source library that implements a user interface for image generation workflows and provides a flexible python api suitable for experimentation. We hope these contributions will achieve two main goals: i) provide a thought framework to inform the creation of human-centered user interfaces for the wide variety of **IGM** systems being created today ii) provide a flexible prototyping tool (*Peacasso*) that supports research and industry applications of image generation models.
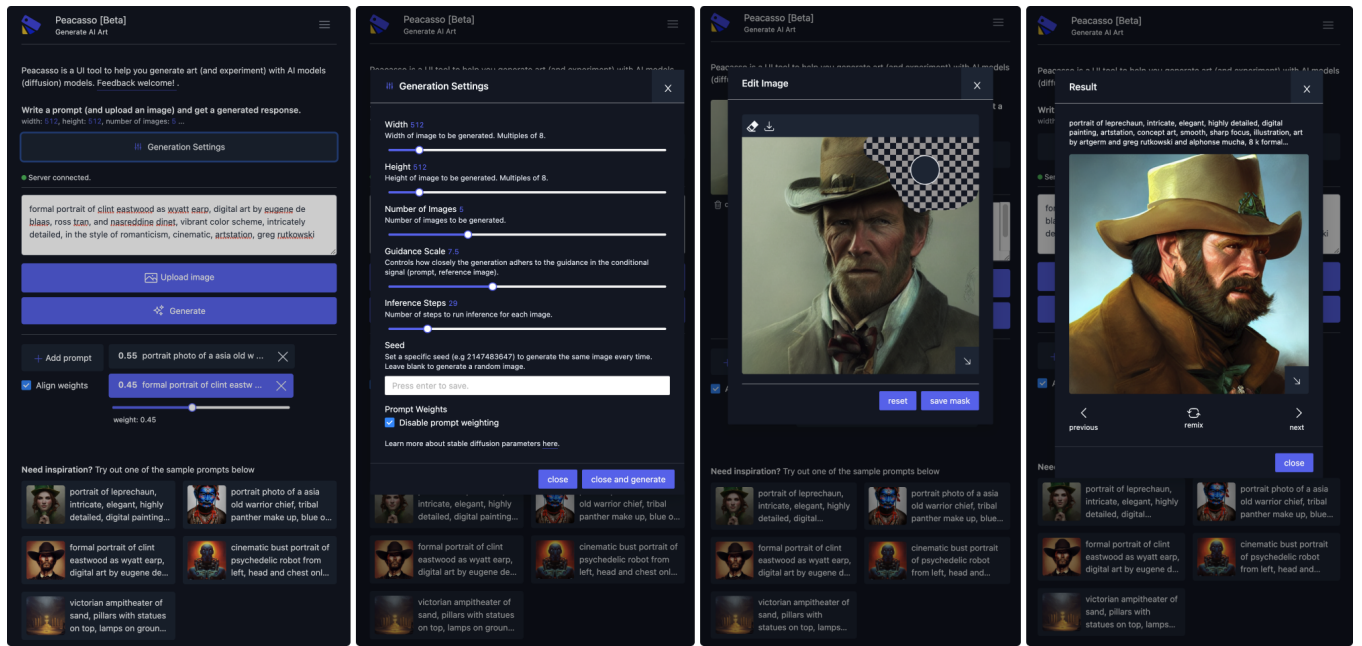
Figure 3: Vertical screenshots of the *Peacasso* Interface. (a) Prompt weight mixing interface (sliders to weight multiple prompts) (b) Generation settings (c) Image inpainting experience to erase parts of an image (d) Gallery view where the user can "remix" a generated image as input to a new generation request.

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