Prompting for Discovery: Flexible Sense-Making for AI Art-Making with DreamSheets

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ABSTRACT

Design space exploration (DSE) for Text-to-Image (TTI) models entails navigating a vast, opaque space of possible image outputs, through a commensurately vast input space of hyperparameters and prompt text. Minor adjustments to prompt input can surface unexpectedly disparate images. How can interfaces support end-users in reliably steering prompt-space explorations towards interesting results? Our design probe, DreamSheets, supports exploration strategies with LLM-based functions for assisted prompt construction and simultaneous display of generated results, hosted in a spreadsheet interface. The flexible layout and novel generative functions enable experimentation with user-defined workflows. Two studies, a preliminary lab study and a longitudinal study with five expert artists, revealed a set of strategies participants use to tackle the challenges of TTI design space exploration, and the interface features required to support them – like using text-generation to define local "axes" of exploration. We distill these insights into a UI mockup to guide future interfaces.

CCS CONCEPTS

• **Human-centered computing → Interaction paradigms**.

ACM Reference Format:

Shm Garanganao Almeda J.D. Zamfirescu-Pereira Kyu Won Kim Pradeep Mani Rathnam Bjoern Hartmann . 2024. Prompting for Discovery: Flexible Sense-Making for AI Art-Making with DreamSheets. In *Proceedings of arXiv Preprint*. ACM, New York, NY, USA, 13 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

1 INTRODUCTION

Text-to-Image (TTI) models like DALL•E [33] and Stable Diffusion [37] generate images from a combination of text prompts and numerical parameters (e.g., random seeds). Such models are wide adoption in a variety of settings, from marketing collateral to independent art making.

A critical skill for users of Text-to-Image (TTI) models is understanding the relationships between prompt text inputs and image outputs. Building such an understanding is neither trivial nor straightforward [48, 49]: the spaces of possible inputs and outputs are *massive*, and the mapping of one to the other is highly *opaque*.

Current patterns in commercial interfaces present limited support for exploration: a text box for prompt input and an area for displaying and saving a few output images. Some offer a number of additional features to support *prompt-engineering*: canned prompt ideas, including options to influence "style," and sliders for manipulating hyperparameters.

This lack of explicit interface support has led to the creation of resources such as community-curated prompt books [28], spreadsheets [46], and tutorials [27, 39] that document exploration processes. Researchers have also begun to study prompting practices [3, 16, 21] and to propose alternative interfaces for interacting with TTI (e.g., Promptify [2]) and other types of generative models (e.g., GanZilla [9], Spacesheets [24]). These systems tend to support particular prompt-image workflows, supporting users in refining prompts towards a goal.

In this paper we argue that supporting Text-To-Image users goes beyond ensuring that they can achieve a particular end result: *gaining an understanding of the mapping between input and output is core to successful co-creation with generative AI systems.* Exploring the relationship between TTI inputs and outputs is a sensemaking process [31, 38] where users aim to build mental representations that allow them to reliably produce desired outputs. While the input and output spaces are massive and opaque, they are *not* arbitrary: prompters *can* develop reliable "navigation" strategies with thoughtful observation and experience. By evaluating many input-output examples, users can begin to sense patterns, learning to predict *where* their prompt will map to in output space, through a particular model. They can then use this information for crafting and steering inputs towards desirable results.

Thus, our guiding research question is: *How might new interfaces best support users in sensemaking for successful art making with such models?*

To investigate this question, we built DreamSheets, a tool that enables TTI users to develop their own exploration strategies within a spreadsheet interface. In DreamSheets, spreadsheet cells can contain prompts, or images generated from those prompts. A set of novel prompt manipulation functions enable users to explore prompt space through the construction and strategic combination of categorical lists, alternative wordings, embellishments, synonyms, and more. These functions are implemented through prompts to a large language model (LLM).

Spreadsheets may not readily provide the ideal affordances for organizing imgage collections; however, they are a *highly flexible* substrate for *what-if* exploration; by presenting image and text generation tools within a customizable sandbox, DreamSheets

arXiv Preprint,
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ACM ISBN 978-x-xxxx-xxxx-x/YY/MM.
https://doi.org/10.1145/nnnnnnn.nnnnnnn

enables users to define their own workflows for sensemaking with formula construction and layout design.

We investigated users' exploration strategies in two studies with DreamSheets: a 1-hour lab study with 12 primarily amateur participants, and a two-week longitudinal study with five expert TTI artists. In these studies, we examined how both groups (1) develop intuition for prompt designs that yield specific outputs, and (2) use DreamSheets's affordances for computational prompt manipulation, workflow creation, and output evaluation. Our primary insights lie in:

(1) Observing patterns in the user-defined strategies and support structures utilized by participants in DreamSheets throughout their TTI exploration journeys, as they discover new creative directions and shift creative control to and from the generative system; and
(2) How the sensemaking insights and skills users develop as they sample information across input and output space interact with visual communication skills, critical for success in prompt-image domains and, potentially, beyond.

We use these insights to generate a UI mockup to inform potential future interfaces, and report on feedback on these mockups from our participants.

Our contribution is three-fold:

(1) DreamSheets, a flexible platform for exploring the joint design space of prompts, seeds, and other TTI hyperparameters.
(2) The first (to our knowledge) longitudinal study of experienced artists using TTI models, focused on understanding how artists use these models and how they make sense of the prompt design space.
(3) A set of UI design suggestions, co-designed in a visual UI mock-up with our artist participants, to enable the kinds of sense-making they pursued while working in DreamSheets.

2 RELATED WORK

Our work here builds on prior research showing that considering many alternatives in parallel can effectively aid design space exploration [14, 34], such as through gallery interfaces [26], tracking exploration history [15, 18], offering suggestions for possible input shifts [26], and effective organization [25, 36, 45]. Spreadsheets enable many of these abilities where commonly-used TTI interfaces lack them.

In this section, we draw explicit connections with Creativity Support Tools, prompting and other TTI model workflows, design space exploration of images in non-TTI contexts, and sensemaking.

2.1 Creativity Support

In 2007, Shneiderman identified four underlying design principles for creativity support tools (CSTs): *support exploratory search*, *enable collaboration*, *provide rich history-keeping*, and *design with low thresholds, high ceilings, and wide walls* [41]. A more recent body of research explores how CST design can aid users' creative processes and productivity [5, 10]. Spreadsheets are themselves an example of a tool that supports creative exploration, enabling users to separate fixed values from values they want to vary, affording effective exploration and evaluation of "what-if" scenarios [35, 41].

2.2 Prompting & Text-to-Image Model Workflows

At the surface, prompting can appear straightforward, but crafting effective prompts is a challenge [22, 48, 49]. How a prompt directly impacts model outputs is an active area of research [20, 40]. Choosing the right language to achieve desirable visual results in these prompt-based interactions can be difficult, presenting challenges for users seeking to reliably harness TTI systems towards creative goals[49]; this has motivated online user communities [8, 32] and researchers to develop and investigate new prompting techniques [22, 23] and tools supporting prompt discovery and exploration [2, 12]. These tools tend to be goal-driven, helping artists elicit the images they already have in mind, and showing them alternatives—rather than explicitly supporting sensemaking as DreamSheets does.

2.3 Design Space Exploration of Images

These prompt discovery tools in fact continue a long line of research into design space exploration of images. When visual judgment of an artifact produced by a human designer is the primary method of evaluation, as it is in computer graphics and animation, prior work has often focused on browsing interfaces, such as in Marks et al.'s seminal Design Galleries [26]. Interaction techniques for browsing include multi-step galleries [26]; map metaphors [43]; or faceted browsing [13]. Narrowing down from the explored designs, users may wish to pursue multiple alternative options for deeper exploration, though typically many orders of magnitude fewer than the number of algorithmically explored designs, as in GEM-NI [47].

Spreadsheets' usefulness for visual design space exploration in part stems from the intrinsic 2D matrix layout enabling "small multiples", a term Edward Tufte popularized [44] as an answer to the question "compared to what?" In a 2D matrix, a large number of images can be readily compared with each other, and the best candidate images identified. Spreadsheets have a rich history of serving as vehicles for exploratory work, in accounting and far beyond−−utilized as early as 1994 for information visualization of data and images themselves [4, 19], including images generates from a numerical input space [24]

2.4 Sensemaking

A number of our observations relate to the broader sense-making literature, including Pirolli and Card's seminal work on information foraging [30]—DreamSheets offers users an *information scent* on prompts—and sensemaking more broadly [31, 38]. This line of work models how users navigate and make decisions in information-rich environments (like DreamSheets), balancing between the perceived cost of seeking information and the potential reward of finding what they're seeking. DreamSheets's design draws upon the *free energy principle of the brain* theory from cognitive science [11] which describes how the brain reduces uncertainty by making predictions and updating an internal mental model accordingly, generatively optimizing its internal model with sensory input to enhance prediction accuracy. This principle formed a basis for Davis et.al's Creative Sense-Making (CSM) framework [7], which they applied to human-AI co-creation in the collaborative drawing domain. DreamSheets's design also draws inspiration

Function Name	Description
TTI(*prompt, [seed], [cfg]*)	Generate an image (at the returned URL) using the given *prompt* and, optionally, *seed* and a classifier-free guidance (*cfg)* parameters.
GPT(*prompt*)	LLM function for arbitrary *prompt*.
GPT_LIST(*prompt, length*)	Populates *length* cells in a row (or column) with words/phrases of type *prompt*.
LIST_COMPLETION(*prompt*)	Like GPT_LIST, but *prompt* is a list of items, rather than a description.
SYNONYMS(*prompt*)	Generates a list of synonyms.
ANTONYMS(*prompt*)	Generates a list of antonyms.
DIVERGENTS(*prompt*)	Generates "divergent" words.
ALTERNATIVES(*prompt*)	Generates a list of alternative wordings for *prompt*.
EMBELLISH(*prompt*)	Generates an embellished alternative to *prompt*, commonly using more specific or detailed words.

Table 1: The LLM-based functions available in our prototype. Each list-producing function additionally has an _T alternative (e.g., SYNONYMS_T) that transposes the output into a column.

and lessons from existing sensemaking interfaces – including classics like Scatter/Gather [6] and more modern implementations like Sensecape [42].

3 PROMPT & IMAGE EXPLORATION WITH DREAMSHEETS

DreamSheets leverages the spreadsheet model in support of iteration and exploration of the TTI generation prompt input space. The features of DreamSheets are embedded within a spreadsheet (built on Google Sheets) that recomputes and re-renders images, allowing drag-based "autofill" and other common spreadsheet functionality. DreamSheets offers access to diffusion model image generation as a spreadsheet function that can take the content of other cells in the sheet as input, including combinations or transformations of multiple cells. These features support the user in efficiently exploring, observing how generated outputs are influenced by modifications to the input.

To aid prompt exploration, our prototype also includes a set of LLM-based functions for manipulating prompts directly, including GPT_LIST and LIST_COMPLETION for generating or extending a list of items of a certain description, EMBELLISH to create a detailed variation of the input text, and ALTERNATIVES to generate multiple variations of a seed prompt (see Table 1 for a full list).

3.1 Design

From a design perspective, integrating TTI model functionality was relatively straightforward—we devoted significant design energy to developing a set of prompt exploration functions (see Table 1), themselves based on prompting a LLM.

Drawing on prior work in prompt design, we identified the testing of alternative phrasings and the addition of detail as core activities in TTI prompt exploration [22, 28]. These activities help users explore neighboring points in design space and recognize fruitful *directions for further* prompt explorations. We operationalized support for these activities as the ALTERNATIVES, DIVERGENTS, and EMBELLISH functions. Similarly, synonym and antonym generation are core NLP building blocks, useful for creating variation that targets specific wordsin a longer prompt—we integrated these capabilities through the SYNONYMS and ANTONYMS functions.

Critically, to use these concepts in a spreadsheet paradigm and support the generation of *sets* of images, we designed these functions to output *lists* of values that populate across a column (or row) of cells. These variations can be referenced by cell in traditional spreadsheet style and used as prompts, or concatenated with other values to form longer prompts.

We also provided functions to *extend* lists of prompts or prompt parts, allowing users to build on a conceptual list by providing a few initial examples.

3.2 DreamSheets Implementation

We explored different services to provide the underlying spreadsheet functionality for DreamSheets, including building our own spreadsheet interface from scratch, open source spreadsheets HandsOnTable[1] and LuckySheet[2], and both Excel and Google Sheets.

One major challenge in integrating with an existing spreadsheet is the relatively long latency of image generation itself: up to 15 seconds or more, even when using cloud APIs. Spreadsheet users are accustomed to rapid updates and recomputations in response to changes in cell values—a multi-minute delay resulting from a backlog of image prompt updates and, consequently, new image generations, would be unacceptably slow. This need drove our use of the Stability.ai API,[3] which supports parallel image generation requests with the Stable Diffusion 2 model, and offers sub-15 second response times. This critically enabled the full-scale "small multiples" visualizations of results that we wanted users to be able to utilize to view and evaluate results across multiple input axes simultaneously.

Ultimately, we selected Google Sheets as the spreadsheet interface, as it is easily extensible and accessible to most people. Google Sheets' Apps Script environment lets developers create add-ons in a JavaScript-like environment, has a sufficiently long timeout (30 seconds) for custom functions, and allows users to continue to edit the sheet even while our custom formulas, which required back-end calls to TTIs and LLMs, awaited responses.

As a side benefit, because Google Sheets is already an online-native platform, rapid collaboration and version history are built-in.

We implemented DreamSheets as a Google Sheets Apps Script add-on and a proxy web server written in JavaScript using ExpressJS. The add-on adds custom functions described in Table 1, making the corresponding requests to the proxy web server which

[1] https://handsontable.com
[2] https://github.com/dream-num/Luckysheet
[3] https://api.stability.ai/docs

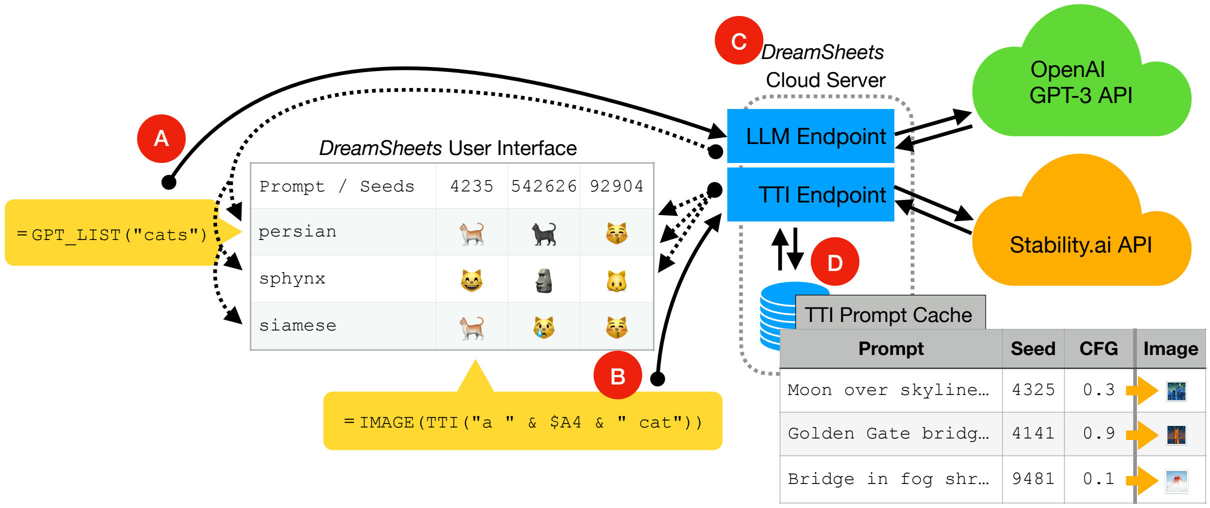


Figure 1: The DreamSheets implementation. LLM (A) and TTI (B) functions fetch from separate endpoints of the DreamSheets cloud server (C) which forwards requests to the OpenAI ChatGPT and Stability.ai Stable Diffusion cloud-based APIs. TTI requests are cached (D) using a hash of (prompt text, seed, classifier-free guidance) as a key.

handles caching and calling the appropriate API to either Stability.ai or OpenAI. Figure 1 illustrates how the proxy server facilitates communication between the Google Sheets add-on and Stability.ai or OpenAI. For the TTI function, the proxy server makes a hash using a combination of the prompt, seed, and guidance values and checks if the image has been generated before. Otherwise, an API call is made to Stability.ai to generate a 512×512-pixel image which is then cached in the file system for easy retrieval in the future.

The LLM-based functions that return a list utilizes OpenAI's ChatGPT with `gpt-3.5-turbo`. To ensure that ChatGPT returns a properly formatted list with the appropriate length, it is initialized with the following messages:

```
system: Respond with a Javascript array literal with
the given length in parentheses
user: types of animals (length: 5)"
assistant: ["dog", "cat", "frog", "horse", "deer"]
user: [PROMPT] (length: [LENGTH])
```

The implementation for each LLM-based function differs only in the prompt sent to the LLM proxy server: each function prepends different additional instructions to the user's inputted prompt. The complete list of full prompts sent to ChatGPT are:

- **LIST_COMPLETION** `Similar items to this list without repeating "[LIST]"`
- **SYNONYMS** `Synonyms of "[USER INPUT]"`
- **ANTONYMS** `Antonyms of "[USER INPUT]"`
- **DIVERGENTS** `Divergent words to "[USER INPUT]"`
- **ALTERNATIVES** `Alternative ways to say "[USER INPUT]"`
- **EMBELLISH** `Embellish this sentence: [USER INPUT]`

4 METHOD

Having built DreamSheets, we first ran a preliminary 1-hour lab study with novice users to understand how users approach using DreamSheets for TTI exploration; this revealed that DreamSheets enables a variety of custom workflows, but that sensemaking was nearly always among the first activity participants engaged in.

Following this study, we ran a second, 2-week longitudinal study with expert users. This second study was intended explicitly to better understand the kinds of custom workflows experts would build for sensemaking, given enough time, and what kinds of individual activities those sensemaking workflows consisted of.

4.1 Preliminary Lab Study

In this initial study, we sought to observe how participants used DreamSheets to define and use a text-to-image generation workflow; we gave participants a concrete task and training in the tool, but did not direct them beyond that.

4.1.1 Participants. We recruited 12 participants via email lists and social media. All 12 reported some spreadsheet experience, with most (10 out of 12) reporting frequent use (many times or daily). 10 out of 12 participants also had some experience with TTI models, and only 1 participant (P1) reported no prior experience with LLMs.

4.1.2 Task and Protocol . Each study took place through a Zoom call that lasted approximately 60 minutes, during which participants and the facilitating researcher collaborated in a shared Google Sheets document. We designed a *concept art* creation task to give users a direction achievable in the short amount of time provided, while leaving room for subjectivity and creativity: users were given a single inspirational image, then asked to generate three new images that could fit in a style and unspecified narrative as suggested by the inspiration image. We included a prompt explaining the task in the activity sheet, as well as an image of a post-apocalyptic, ruined Seattle, complete with space needle[4] (see Fig. 2, cell B3).

[4]This image was borrowed with gratitude from Andy Salerno, whose blog post [39] originally inspired this work.

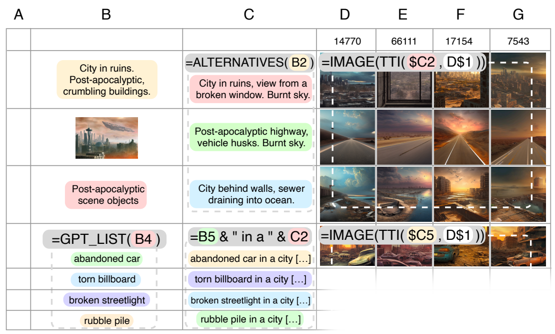


Figure 2: DreamSheets in typical use. Gray lozenges show user-entered formulas, while dashed lines show cell values containing computed or generated content. Here, an initial prompt (B2) is expanded using =variations into column (C2:C4). Together with a row of seeds (D1:G1), this yields a set of images (D2:G4). Further exploration is enabled by =gpt_list (B5:B8) and concatenation (&) into new prompts (C5:C8).

Our protocol began with a brief tutorial to DreamSheets and its functionalities, followed by an observation of participants as they engaged in the concept art task. We used an example sheet to walk participants through a tutorial to first remind participants of general spreadsheet operations (i.e. using formulas with cell references and expanding them with autofill) and then introducing DreamSheets's image and text generation functions. Once users were comfortable using the TTI and GPT functions, we introduced the concept art activity. Participants were encouraged to think aloud as they generated the three images required to complete the task.

4.1.3 Data Collection and Analysis. We observed, recorded, and transcribed video and audio of each interview, including the $\tilde{4}0$ minutes of system use, in entirety, throughout which participants were encouraged to think aloud and provide clarification when prompted. We then engaged in an exploratory qualitative data analysis using the recordings, transcripts, and resulting spreadsheet artifacts. We recorded responses to surveys completed before and after the interview, and reviewed usage data, containing logs of each text or image generation function call used in DreamSheets.

4.1.4 Preliminary Study Results: DreamSheets in use. Here, we provide an overview of some results specific to the preliminary lab study, which informed our second, longitudinal study.

We discuss usage patterns and themes informed by *both* studies in sections 5 and 7.

More than half of the participants in this study (7 out of 10) reported limited to no experience with TTI systems, but *all* participants were able to successfully utilize a prompt-crafting workflow in the DreamSheets system, and to produce generations that they were satisfied with for the concept art task. Though authored directly by participants, the workflows adopted by more novice participants were likely inspired by the example structures showcased during the initial tutorial phase, with P3 and P4 copying from the tutorial examples directly.

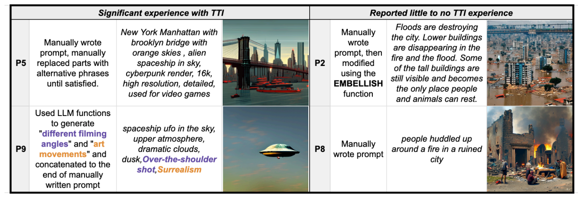


Figure 3: Examples of prompts authored by participants in the first study

The seven participants with limited prompt-engineering experience (P1, 2, 3, 4, 6, 8, 10) wrote their prompt in "English" ranging from brief sentence fragments to detailed scene descriptions. Meanwhile, 4 of the 5 participants who reported substantial or extensive TTI experience (P5, P7, P9, P11) wrote in a structure specific to "prompt language" – comma separated lists of terms, including modifiers to influence visual style. Novice and experienced participants found LLM-based functions useful for creating or improving their prompts.

Participants with more spreadsheet experience more readily adopted string concatenation strategies to construct prompts. Using LLM-based functions to generate a series of words in a particular category, like GPT_LIST(camera angles) or synonyms("red"), participants could introduce *word-level variation* to a manually authored prompt or prompt structure. We describe this *LLM-assisted dynamic prompt construction* as a prompt-space exploration strategy in Section 5.2.

This formative study confirmed DreamSheets's usefulness as an exploratory TTI system and illuminated promising usage patterns, as we observed even novice participants begin developing various strategies and structures to support their task completion goals in the $\tilde{4}0$ minutes provided. However, the brevity and constraints of this first-use study format prevented users from fully leveraging functionality of DreamSheets to develop strategies for user-defined goals. This encouraged the longitudinal study to observe how experienced generative artists might utilize DreamSheets to craft workflows towards "real-world" creative goals.

4.2 Longitudinal Expert Study Design

We turned to a longitudinal study to better understand the kinds of custom workflows experts would build when given the time and flexibility to pursue authentic creative goals.

4.2.1 Participants. To recruit experts for our second user study, we sent recruitment messages to individuals publicly participating in generative art communities on social media, and recruited 5 individuals (designated as E1-5 to differentiate from Study 1 participants).

4.2.2 Protocol. We conducted three 45 minute interviews spanning 2 weeks with each participant. Participants were instructed to use the tool for $\tilde{7}$-10 hours over the course of the 2 week study. We suggested 30-45 minutes of tool use per day to fulfill this, but participants were given the freedom to decide the length and structure of their work sessions.

As with the first study, the initial interview began with a short tutorial reviewing spreadsheet functionality and demonstrating

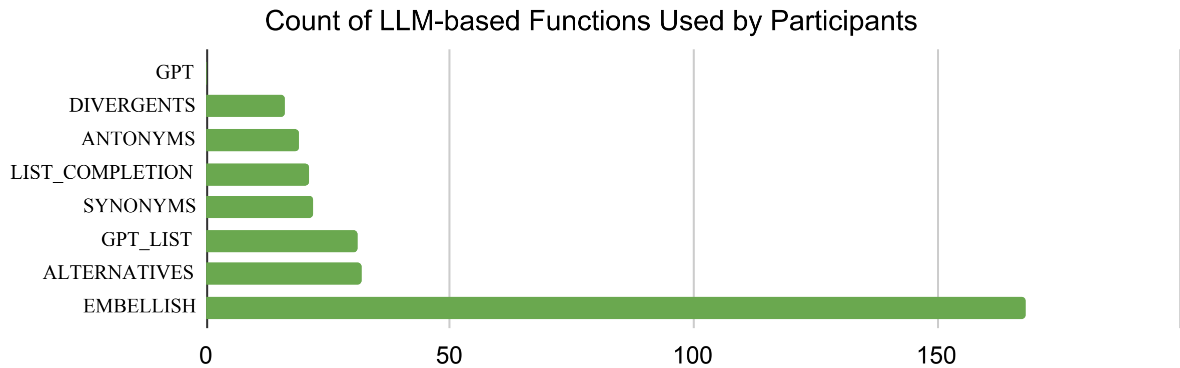


Figure 4: Number of times participants used each of the LLM-based functions during the activity in our preliminary lab study.

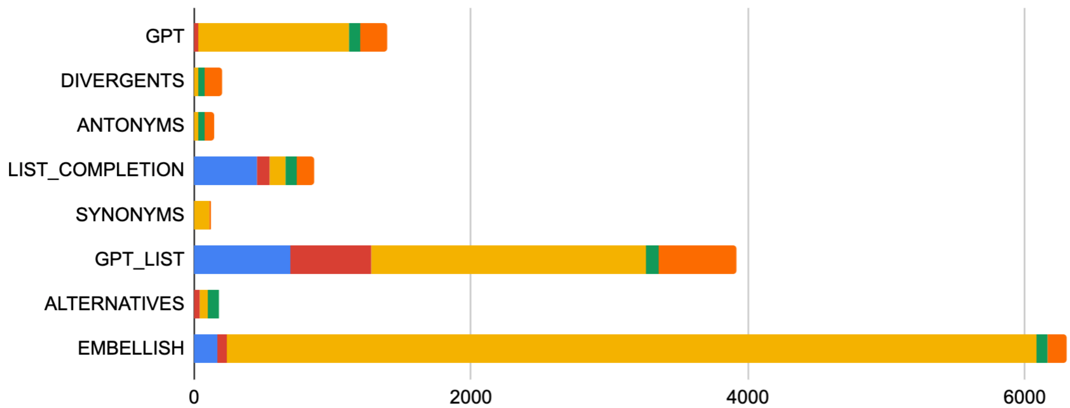


Figure 5: Number of times participants used each of the LLM-based functions the two weeks of our longitudinal expert study. Individual colors represent individual participants consistently across functions (5 total).

DreamSheets functions. The collaborative spreadsheet shared with each participant included documentation and examples of DreamSheets function use. Participants could contact the research team via email if they had questions throughout the study.

The second interview took place 1 week into the study. We asked participants to explain their exploration goals and strategies, and to use relevant parts of their spreadsheets to illustrate. We described back to participants our observations, allowing them to clarify any potential misinterpretations of their actions.

Based on the feedback we received, we designed a UI mockup that incorporated elements inspired by the structures built and functions used by participants during their first week of using DreamSheets.

In the third and final 45-minute interview, we again asked participants to describe the creative explorations evident in their spreadsheets, and to explain how they integrated DreamSheets's functionalities into their creative process. We then showed participants the UI mockup to gain their perspective and elicit further feedback and suggestions for designing more supportive TTI interfaces.

Finally, participants were asked to share 3-5 of their favorite generations created using the DreamSheets system, allowing us to better consider which DreamSheets explorations were most "successful" to our participants.

4.2.3 Data Collection and Analysis. We analyzed our participants' usage of DreamSheets as observed or described during interviews, as well as the resulting artifacts: the sheets and usage logs, containing the full chronology of function calls made to the DreamSheets system. We periodically viewed their spreadsheets throughout the 2-week study, including their Version History – a detailed record of changes made to the sheet, which we used to recover and save copies of previous versions.

We used these sources to identify participants exploratory goals and strategies while using DreamSheets. We identified usage patterns across participants, and considered how workflows adapted throughout user's exploratory journeys in DreamSheets.

5 FINDINGS: OBSERVING USER-DEFINED TTI WORKFLOWS

Across both studies, participants' use of DreamSheets and the artifacts they produced allowed us to observe and identify key elements of their TTI creative workflow: their *goals*, the *strategies*

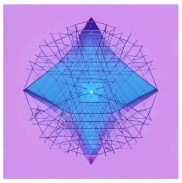
Goal:	Generate flat, "2D vector" style illustrations with different background colors.	
Prompt Template for this Exploration:	=IMAGE(TTI(("flat 2d illustration with clean lines of " & SUBJECT & ", vector svg with a " & COLOR & " background"), SEED))	
Prompts for Selected Images:	flat 2d illustration with clean lines of a crystal, vector svg with a periwinkle background, 7935	flat 2d illustration with clean lines of a mystical orb, vector svg with a periwinkle background, 7935
Selected Images:		

Figure 6: Images generated with the same seed can have visual similarities. E5 explored with goal of locating a seed biased towards generating "a central object" and located 7935. Gaining this information contributed to the success of P5's creative goal to generate "vector" style graphics. These were among their favorite generations.
Green prompt text is manually written by the user.
Orange indicates text pulled from a manually curated list.
Purple indicates LLM-generated text.

they chose to pursue them, and the *actions* (functions, formulas) and *structures*, (spreadsheet layout choices) they elected to utilize.

We identified strategies adopted by TTI users to navigate prompt-image space and describe these findings below.

5.1 Exploration *without* Prompt Manipulation

Prompt-crafting is central to the effective use of TTI models. However, the ability to quickly manipulate, evaluate, and select numerical hyperparameters (the `seed` and `cfg`, or classifier-free guidance) alone provides users of DreamSheets with useful axes on which to scaffold exploration and selection.

Generating many images using the same *prompt* but different *seeds* was a common strategy across participants in both studies.

All 5 expert participants utilized seed variations to quickly evaluate many "versions" of the same prompt. A seed variation based exploration strategy allows the user to quickly reveal a series of visually diverse outputs without having to engage in the mental effort required to edit prompt language.

Technically, seeds define the specific random noise that the diffusion model will use as a starting point; the model then repeatedly "de-noises" successive versions, to generate an image, with the text prompt acting as a guide. Thus, while there is no perceptual correlation between adjacent seeds, images generated with the same seed may share certain visual similarities to the original noise pattern.

E5 explored possible seeds with a particular sense-making goal: locating a seed that would bias the image generation to feature "a central object" on a flat background. P5 found **7935** after trying only a few different seeds in DreamSheets, and used this value in many other explorations (see Figure 6).

E2 and E5 were particularly interested in exploring different `cfg` values. E2, E3, and E5 developed an exploration structure equivalent to creating a "slider": delegating a cell for a specifying a guidance value, then regenerating with different guidance values before choosing an ideal "setting."

All participants tried organizing generated outputs in a 2D matrix "contact sheet" layout (as described by P1), and 3 of the 5 experts (P1, P4, P5) explicitly remarked on its usefulness. These explorations allowed users to make sense of available options in a local area, recognize interesting values, and leverage this information towards more successful future generations.

Overall, all participants manipulated hyperparameters, allowing them to travel along one dimension at a time through input space, learning the idiosyncracies of a particular image generation model's output space along that axis, separate from the complexity introduced by prompt manipulation.

5.2 Dynamic Prompt Construction

> "Does Stable Diffusion know the same artists I do?" (P11)

Participants manipulated language to make movements in prompt-space that would, ideally, translate into movements towards more interesting areas of image-space.

One common sense-making strategy we observed across both studies: participants make local edits to key descriptive words within an initial prompt. By constructing conceptually similar alternatives, participants tested the effects of specific words or phrase within a larger prompt. For example:

> A twisted man that exists purely to seek revenge and **consume power**

...is manually edited to:

> A twisted man that exists purely to seek revenge and **is on the edge of death**

...and finally to:

> A twisted **ghoulish** man that exists purely to seek revenge and is on the edge of death

These manually written prompts were passed to TTI() by E4 in the same exploration session; E4 generated 8-10 versions of each prompt, using different seeds for variation, before iterating on the prompt text, noting:

> "Ghoulish was a word that helps, so I kept using that word." (E4)

Even novice participants recognized the need for this kind of exploration; P6, a novice user with limited prompting experience, said:

> "I think it's good to know how things change depending on different variables... the spreadsheet helps with navigating what exactly is changing within the image." (P6)

In DreamSheets, participants can engage in this iterative, exploratory prompt-editing process with the aid of DreamSheets's LLM-based functions and spreadsheet concatenation, streamlining the discovery of useful points in prompt-space.

5.2.1 Prompt Templates and Axes. Participants utilized lists of words that could swap into specified "slots" in longer prompts,

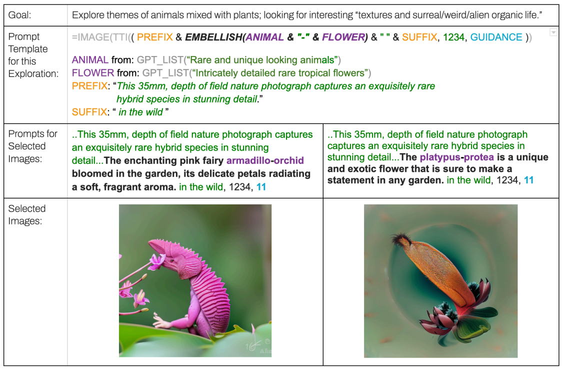


Figure 7: E3 is interested in generating animal-plant hybrids in their textured film photography style. They first created a "settings panel" structure in their sheet, delegating a cell for each desired input component. They used a combination of LLM list functions and concatenation to construct a dynamic prompt template. Changing any of the input cells regenerated the displayed image results, allowing them to experiment – e.g., entering different guidance values until settling on 11.

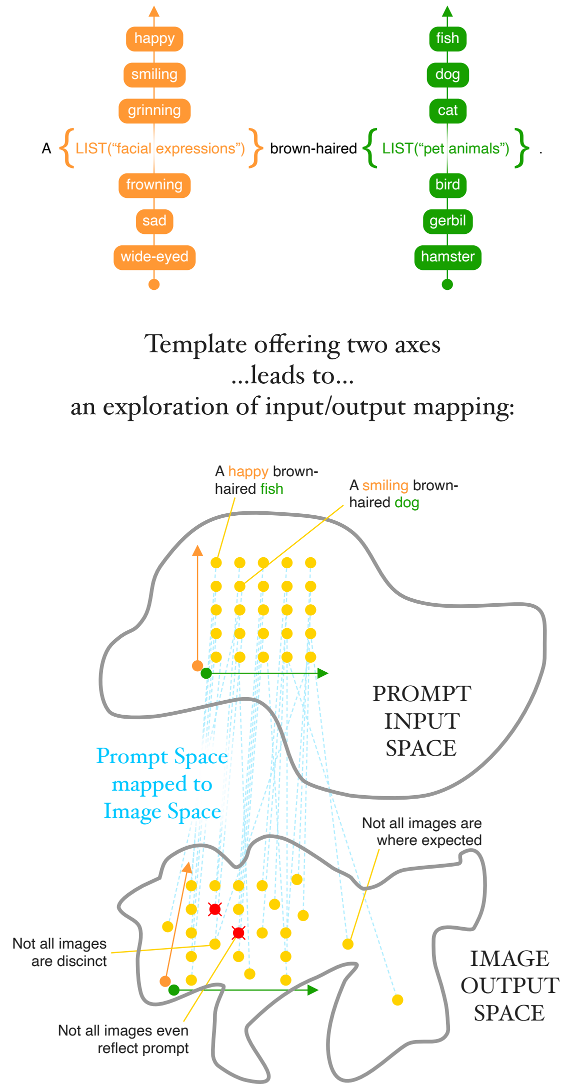


Figure 8: Prompt templates can offer "axes" of exploration for sensemaking; these axes then also map (often imperfectly) from the prompt input space to the image output space, as illustrated here.

authoring a type of dynamic, concatenated "prompt template" structure. These lists can be constructed manually, or by using one of the list-generating LLM functions in DreamSheets.

By referencing from multiple categorical lists, participants select semantic "axes" to define a 2D prompt space for exploration: expert participant E1 used an LLM generated list of *facial expressions* and a manually curated list of *subjects* (girl, dog, cat) together to explore and understand how individual facial expressions interacted with individual subjects (see Figure 8 for an illustration). These "axes" were neither numerical nor ordinal, but provided a useful sensemaking structure; E1 discovered that a "smiling dog" would not, in fact, smile—but that a "grinning dog" did.

E1 also used concatenation to append `", well lit, studio photography, portrait"` to each prompt in this sheet, titled "*Expressions Exploration 1*," explaining that grounded the results of their exploration in a *consistent "default" style*. They intended to use the information they gained about effectively "prompting for emotions" to improve future generative art pieces where aesthetic style is part of their creative goal.

5.2.2 LLM Function Use & Workflow Structure. All of our expert participants used the LLM functions to some extent, including E4 and E5, who typically preferred to manually craft their prompts or rely on hyperparameters to create variation. 4 of 5 experts (E1, E2, E3, E5) utilized cell concatenation to craft dynamic prompt templates with LLM-generated prompt parts. E4 used LLM-generations to suggest new ideas in a particular category, e.g., ideas for unique *camera angles*. See Figures 4 and 5 for counts of how frequently participants utilized each of the LLM functions across both studies.

For 3 of 5 expert participants (E1, E2, E5), the LLM-based list generation functions gpt_list and list_completion comprised more than half of their LLM Function use. E3 also used these list generation functions many times—in fact, more than any other participant—but their use of DreamSheets stood out overall: E3 made 9268 LLM function calls, 7.6 times more than the next most frequent user of the LLM functions; including 5851 embellish calls. See Figure 7 for a sample of the sophisticated text-manipulation workflow they developed.

E1, E2, and E3 were interested in using prompt text primarily or entirely generated by the LLM functions. Both E2 and E3 developed a structural strategy that involved explicitly designating an area of their sheets for generating and manipulating lists of text, an area for systematically combining values these terms into full prompts, and an area for displaying the resulting images.

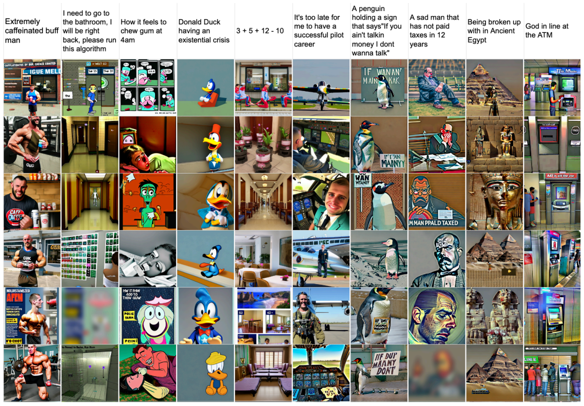


Figure 9: A small subset of the full (32 prompts x 13 seeds) exploration that E4 generated in a single session with DreamSheets. They attempted to generate more focused images towards a concept art creation goal, but much preferred generations in this exploratory set.

With LLM-functions for automatically generating points along a semantic axis, users can quickly experiment with axes in prompt space without having to formulate their own prompt word ideas - they can choose *camera angle* as a "slider" to explore, then pick their "favorite setting" from the generated results - without having to recall the words to describe it.

5.2.3 Facilitating discovery by relinquishing creative control. E4 much preferred using DreamSheets to generate from "random" concepts with the goal of seeing "how the AI interpreted very vague and unlikely prompts." In this setting, relinquishing control over the image generation to the system was welcomed. E4 chose only results from this type of "random exploration" (see Figure 9) to share at the end of the study.

AI-generated creative content inherently introduces unexpected results that users may not have considered; users can take advantage of this by handing their creative-decision making labor—and control—to a generative system.

As the LLM-based functions are nondeterministic, they may generate different text each time the sheet is reloaded. E2 and E3 embraced this nondeterminism. E3 was explicitly satisfied with new generations appearing whenever they reloaded the sheet, each following their chosen prompt structure and style, while featuring novel prompt parts injected by the LLM functions. E1 and E3 interrupted the nondeterminism by "setting" results- when particularly satisfied or interested in a given prompt part generated by the LLM, they manually edited or copied these cells as raw text to prevent regeneration of the related prompts and images.

When engaging in a co-creative generative process, users choose when to introduce unexpected variability, and when to take back creative control. In both studies, participants utilized the LLM-based functions to introduce a *range* of variation to their prompts: from prompts entirely generated by the LLM, to generating only single word (i.e. color) – or, rejecting the LLM-generated suggestions altogether and manually overwriting them.

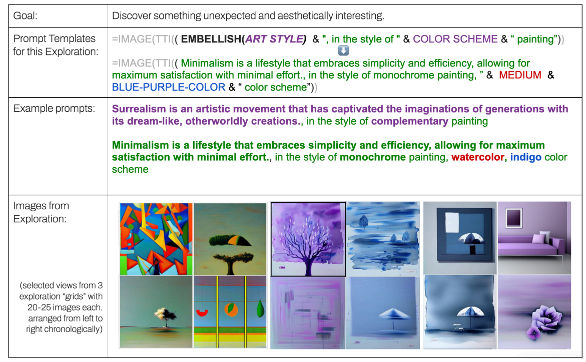


Figure 10: E1 began this exploration with a prompt almost entirely constructed with LLM-generated text. After evaluating the selection of outputs for visually interesting results, they copied these promising prompt terms to new cells. They began a new exploration, progressively appending additional dynamic terms, then "setting" them. They selected the image outlined in black as one of their favorite images generated during the study, and went on to use the "monochromatic" and "watercolor" prompt terms they discovered to direct many future generations towards a pleasing aesthetic.

E1 selected the image outlined in black in Figure 10 as one of their favorite images generated during the study; the exploration process that led to this image exemplifies how users leverage DreamSheets's flexibility to shift creative control to and from the generative system, as they responded to new discoveries and creative directions. At first, E1 had no particular idea in mind, approaching DreamSheets with the goal of discovering something novel and unexpected. This inspired them to craft a prompt template almost entirely comprised of LLM-generated text. After generating and evaluating 25 images with this template, they identified an interesting result using a combination of "EMBELLISH("minimalism")" and "monochrome" as its prompt.

At this point, their goals began to shift: these terms provided E4 access to an interesting aesthetic space, and by "setting" them, E1 could explore a promising local "patch."

> "These pieces showcase the unexpected, delightful results I got during this study! I didn't set out to make pixel art or watercolors, but through the course of the study I discovered these aesthetic spaces that I really loved!" (E1)

E1 continued to use the "monochromatic" and "watercolor" to direct future explorations towards this appealing aesthetic space, and used these terms to generate several of their favorite images.

All expert participants alluded to "discovery" being a part of their motivation to use generative art tools, and something that DreamSheets's exploratory features supported well. E5 described themselves as "hardly ever prompting with intention at this point," instead opting to describe their process as "prompting for discovery."

Figure 11: An image selected by P2, using the prompt: "photo taken with a dji camera of Tahiti islands, iceland ultra-wide lens, rembrandt lighting mammatus clouds, HDR photography." They discovered that "DJI Camera" consistently generated aerial landscape photography.

5.2.4 Discovering New Concepts. Sometimes participants discovered new concepts and labels that they had not considered before in their practice.

Consider an exploration session that resulted in one of E2's favorite generated images, Figure 11. This was driven by a desire to generate landscape photography style images of islands. As with other explorations, they concatenated results from several LLM-generated lists to form this prompt, but in this case manually added "photo taken with a dji camera of..." They had discovered that invoking *DJI*, a drone camera company, helped to generate quality aerial images.

> "DJI is this Chinese company that makes drones... when you use that in a prompt, it's ...giving you a really good up in the air perspective... you might use words like, 'aerial shot' or 'bird's-eye view' that don't work as good as saying, 'DJI camera.'
> So a big part of this whole thing, is improving your vocabulary of artistic terms to let you know what kind of references you need to make in a prompt to make the image better." (E2)

6 CODESIGNING THE DREAMSHEETS 2.0 UI MOCKUP

As a final step in understanding how participants viewed their own sense-making processes, and to validate that *we* were gaining an understanding of how to better to support these processes, we developed UI mockups that we shared with participants for their feedback. We included features that were requested throughout our expert participants' use of DreamSheets, including a negative prompt space (see Figure 12).

6.1 Visual Layout

We designed two visual layout settings that users can freely toggle between: a grid view (12, left) and a focused list view(12, right). This was informed by how our participants structured the visual display of images in their sheets: they valued the evaluation affordances of the "small-multiples" contact sheet layout, but viewing results in detail required adjusting column size or "zoom" settings in the spreadsheet. Organizing outputs into an evaluation friendly visual layout facilitates quick recognition of interesting image results.

6.2 "Banking" Prompt Text and Components

Even experienced prompt artists may have trouble keeping the names of their favorite internet aesthetics or lighting styles at hand, and useful prompt components may be lengthy or otherwise difficult to recall.

To that end, we designed a prompt "token bank" system (Figure 12, and featured in Figure 13, right) that would allow users to convert any highlighted prompt text into a *Saved Token* for simple reuse in future prompts. Saved tokens can be further edited and explored, encouraging users to develop accurate and informed sensemaking data. Tokens can also be converted into *dynamic* tokens.

6.3 Dynamic Tokens: Supporting Exploratory Axes

Dynamic tokens take the role of the "slots" used by participants to specify where to introduce text variation into their dynamic prompt templates, while eliminating the need for users to work with cell concatenation. Prompt variations are automatically generated, systematically combined, and populated across several columns of generated images. Users can append, edit, and remove prompt words for each column of exploration, at will. Seeds create the variation in each row, and users can easily randomize all seeds, manually edit them, or generate more.

6.4 Participant Feedback

We used UI mockup design to elicit feedback and speculative ideas from participants. Participants overall reflected positively on the concept of being able to save and recover prompt parts for use in future explorations. E4 compared this to their current strategy of saving prompts in a text document, including frequently used modifiers that help in achieving consistent image styles.

> "If I can drag and drop a presaved dynamic chunk... I can fully focus on sculpting the prompt and being creative." (E4)

Participants, especially E1 and E5, were excited by the idea of a "Save session" feature, and each described a similar expected use case: to save the current state of the system, pausing their workflow to return at a later date. E5 expressed a preference to separate their "generation" process (crafting prompts and generate hundreds, even thousands of images) from their "evaluation" process (curating the selection of images), and described being able to return to a previous exploration at a later date as a potential "game-changer."

Participants had a number of ideas for what an "Explore this image" option could introduce, with the potential to build upon DreamSheets's functionalities to support both broad and focused exploration strategies. These suggestions included: (1) semantic level prompt-image editing in the style of ControlNet [50]; (2) Image-to-Text generation like CLIP Interrogator [29] or Midjourney's `/describe` function [1]; (3) inpainting and outpainting; among several other ideas for focused image-to-image or image-to-text transformations.

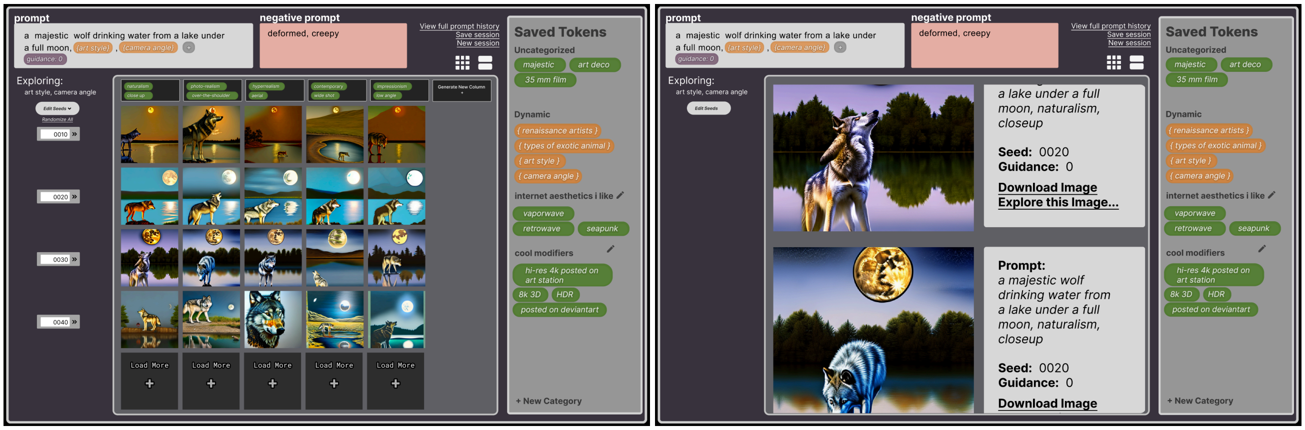


Figure 12: Views of the Dreamsheets 2.0 UI Mockup, showcasing the two visual layouts that users can freely toggle between: a grid view (left) and a focused list view (right). DreamSheets 1.0 users valued the "small-multiples" contact sheet layout, but viewing results in detail required them to change "zoom" settings or tediously adjust the sizes of columns and rows. An improved UI would provide appropriate interface structures to support TTI users as they move between broad and focused evaluations of results,

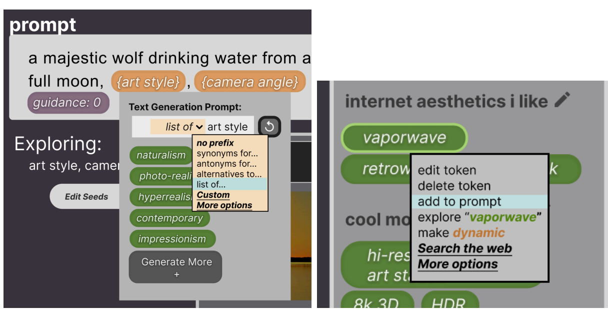


Figure 13: Views of elements featured in the interactive UI Mockup. *Dynamic* tokens fill the role of "slots" used by participants to flexibly introduce text variation into *dynamic prompt templates*, while eliminating the need to write cell concatenation formulas. The LLM used to support this interaction is surfaced; users can control how the prompt is sent. Any word or phrase can be saved as a prompt token; users can explore a term further to gain more informed sense-making data.

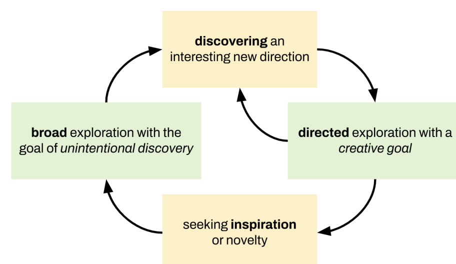


Figure 14: As users explore prompt-image space, they discover interesting new directions to pursue. They can expand their explorations into new directions, or focus their exploration towards promising results. User's co-creative strategies adapt to shifting exploration goals.

7 DISCUSSION

Our findings reveal challenges, tensions, and opportunities in the TTI prompt-exploration process. How can we apply this understanding to guide future exploratory interface designs?

7.1 Prompt Exploration as Foraging

While the sensemaking strategies that TTI users develop as they iteratively sample information across input and output space helps users to develop vocabulary and visual communication concepts that carry to other spaces, new models present entirely new latent spaces to discover and learn how to "prompt for."

TTI interface designers seeking to support the broad exploration and discovery processes necessary to navigate a vast, opaque prompt-image space can reduce users' exploratory "cost" by designing for *Recognition over Recall.* Viewing the outputs of explorations in an expandable "contact sheet" layout, as afforded by DreamSheets, users can efficiently evaluate a wide selection of variations and *recognize* interesting directions from displayed outputs.

With LLM assistance, users can quickly generate individual points to sample along a semantic axis, allowing them to move through a local "patch" in prompt space without needing to manually recall and formulate the right language for this movement - effectively lowering the perceived cost of searching this area of prompt space.

To echo Information Foraging theory [30], we observed participants taking cues from the generated results of previous prompt-space explorations, then estimating the "information value" of a local area in the TTI design space, before making their next move. After trying a particular prompt, users consider how likely they are to discover valuable images in a local "patch," against the perceived effort it would require, and use this to determine whether they should venture deeper, or leave the patch and choose a new direction for exploration. By lowering the exploration cost, such as with LLM functions for assisted prompt-crafing, users can explore *more* and *more widely*. We illustrate stages in the nonlinear exploratory process that TTI users can fluidly move through in Figure 14.

7.2 Shifting the Locus of Control to Match Creative Goals

As TTI users decide whether to expand their search in new directions, or venture into a more focused exploration, flexible options for AI involvement can play a role in fluidly supporting these shifts in goals.

AI-generated serendipity is ideal for expansive search, but when a promising "scent" is unexpectedly identified, the user will want the power and agency to hone in. Such discoveries are, by nature, difficult to predict. Even when users hand off creative-labor, and thus, control, to the inspirational power of AI-generated spontaneity, they can maintain the flexibility to strategically reclaim that control at any time. This tension echoes the challenges observed by Lawton *et al.* in "When is a Tool a Tool?" [17]. Future work should continue to study the way that co-creative systems can either adapt to users' shifting goals, or provide users with the flexibility to choose and self-define where and how a generative tool can influence their workflow.

7.3 Learning Words for the World, through an AI-generated Lens

As TTI users visually observe and evaluate the results of their prompt-space explorations, they learn words that are useful for prompting a specific image generation model. They also develop a sense of visual information that they can carry to other models—and sometimes, the world.

The information latent in text-to-image models becomes more accessible with the help of LLM suggestions, and can go beyond learning better prompt language, towards developing general purpose visual communication skills. As consumer Text-To-Image tools rapidly proliferate, they have the potential to allow users to accessibly learn these visual-semantic associations in practice, including those typically developed through study of visual media history. However, this also surfaces the potential for AI-generated content to proliferate *misinformation with the illusion of majority opinion*, as described by Zhou *et al.* [51] In the case of TTI, inaccuracies—a particular artist's name mapping to the wrong visual style, for instance—could prove immensely challenging to identify and correct. This indicates an avenue for future studies into the potential influence of TTI to influence visual culture, including the potential to amplify existing biases against underrepresented groups in visual history.

8 CONCLUSION

Text-to-Image models challenge users to navigate vast, opaque design spaces on both sides—prompt input and image output. DreamSheets provides a flexible, spreadsheet-based interface for users to author strategies to achieve creative goals, and facilitating sensemaking—developing through experience the language and working understanding needed to reliably steer image generations towards interesting outputs. Through two user studies, including a longitudinal expert study, we observed challenges, tensions, and opportunities in the TTI prompt-exploration process. We utilized these insights to develop a UI mockup, improved with participant feedback, and suggesting features for future supportive TTI exploration interfaces. Finally, we considered the implications of supporting users' sensemaking in prompt-image space, and beyond.

9 DISCLOSURE

The authors used ChatGPT for minor copy editing tasks.

REFERENCES

[1] 2023. Documentation for Midjourney's /describe Function. https://docs.midjourney.com/docs/describe Accessed: 2023-09-15.
[2] 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 UIST 2023*. ACM, 1–14.
[3] Minsuk Chang, Stefania Druga, Alexander J. Fiannaca, Pedro Vergani, Chinmay Kulkarni, Carrie J Cai, and Michael Terry. 2023. The Prompt Artists. In *Creativity and Cognition*. ACM, Virtual Event USA, 75–87. https://doi.org/10.1145/3591196.3593515
[4] Ed Huai-hsin Chi, Joseph Konstan, Phillip Barry, and John Riedl. 1997. A Spreadsheet Approach to Information Visualization. In *Proceedings of the 10th Annual ACM Symposium on User Interface Software and Technology* (Banff, Alberta, Canada) *(UIST '97)*. Association for Computing Machinery, New York, NY, USA, 79–80. https://doi.org/10.1145/263407.263513
[5] John Joon Young Chung, Shiqing He, and Eytan Adar. 2021. The Intersection of Users, Roles, Interactions, and Technologies in Creativity Support Tools. In *Designing Interactive Systems Conference 2021* (Virtual Event, USA) *(DIS '21)*. Association for Computing Machinery, New York, NY, USA, 1817–1833. https://doi.org/10.1145/3461778.3462050
[6] Douglass R Cutting, David R Karger, Jan O Pedersen, and John W Tukey. 2017. Scatter/gather: A cluster-based approach to browsing large document collections. In *ACM SIGIR Forum*, Vol. 51. ACM New York, NY, USA, 148–159.
[7] Nicholas Davis, Chih-Pin Hsiao, Kunwar Yashraj Singh, Brenda Lin, and Brian Magerko. 2017. Creative Sense-Making: Quantifying Interaction Dynamics in Co-Creation. In *Proceedings of the 2017 ACM SIGCHI Conference on Creativity and Cognition* (Singapore, Singapore) *(C&C '17)*. Association for Computing Machinery, New York, NY, USA, 356–366. https://doi.org/10.1145/3059454.3059478
[8] Remi Durant. 2023. Artist Studies. https://remidurant.com/artists/ Accessed: 2023-09-15.
[9] 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*. 1–10.
[10] Jonas Frich, Lindsay MacDonald Vermeulen, Christian Remy, Michael Mose Biskjaer, and Peter Dalsgaard. 2019. Mapping the Landscape of Creativity Support Tools in HCI. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–18. https://doi.org/10.1145/3290605.3300619
[11] Karl Friston. 2009. The free-energy principle: a rough guide to the brain? *Trends in cognitive sciences* 13, 7 (2009), 293–301.
[12] Pol Baladas Gerard Serra, Oriol Domingo. 2022. A programmable interface for creative exploration. *Machine Learning for Creativity and Design Workshop at the 36th Conference on Neural Information Processing Systems (NeurIPS 2022)* (December 2022). https://neuripscreativityworkshop.github.io/2022/papers/ml4cd2022_paper19.pdf
[13] Elena L. Glassman, Tianyi Zhang, Björn Hartmann, and Miryung Kim. 2018. *Visualizing API Usage Examples at Scale.* Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3173574.3174154
[14] Björn Hartmann, Loren Yu, Abel Allison, Yeonsoo Yang, and Scott R. Klemmer. 2008. Design as Exploration: Creating Interface Alternatives through Parallel Authoring and Runtime Tuning. In *Proceedings of the 21st Annual ACM Symposium on User Interface Software and Technology* (Monterey, CA, USA) *(UIST '08)*. Association for Computing Machinery, New York, NY, USA, 91–100. https://doi.org/10.1145/1449715.1449732

[15] Jeffrey Heer, Jock Mackinlay, Chris Stolte, and Maneesh Agrawala. 2008. Graphical histories for visualization: Supporting analysis, communication, and evaluation. *IEEE transactions on visualization and computer graphics* 14, 6 (2008), 1189–1196.

[16] Chinmay Kulkarni, Stefania Druga, Minsuk Chang, Alex Fiannaca, Carrie Cai, and Michael Terry. 2023. A Word is Worth a Thousand Pictures: Prompts as AI Design Material. https://arxiv.org/abs/2303.12647v1

[17] Tomas Lawton, Kazjon Grace, and Francisco J Ibarrola. 2023. When is a Tool a Tool? User Perceptions of System Agency in Human–AI Co-Creative Drawing. In *Proceedings of the 2023 ACM Designing Interactive Systems Conference*. 1978–1996.

[18] Brian Lee, Savil Srivastava, Ranjitha Kumar, Ronen Brafman, and Scott R Klemmer. 2010. Designing with interactive example galleries. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 2257–2266.

[19] Marc Levoy. 1994. Spreadsheets for images. In *Proceedings of the 21st annual conference on Computer graphics and interactive techniques*. 139–146.

[20] Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. 2021. Pre-train, Prompt, and Predict: A Systematic Survey of Prompting Methods in Natural Language Processing. arXiv:2107.13586 [cs.CL]

[21] Vivian Liu and Lydia B. Chilton. 2021. Design Guidelines for Prompt Engineering Text-to-Image Generative Models. https://doi.org/10.48550/ARXIV.2109.06977

[22] 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* (New Orleans, LA, USA) *(CHI '22)*. Association for Computing Machinery, New York, NY, USA, Article 384, 23 pages. https://doi.org/10.1145/3491102.3501825

[23] Vivian Liu, Jo Vermeulen, George Fitzmaurice, and Justin Matejka. 2022. 3DALL-E: Integrating Text-to-Image AI in 3D Design Workflows. arXiv:2210.11603 [cs.HC]

[24] Bryan Loh and Tom White. 2018. SpaceSheets: interactive latent space exploration through a spreadsheet interface. (2018).

[25] Aran Lunzer and Kasper Hornbæk. 2008. Subjunctive Interfaces: Extending Applications to Support Parallel Setup, Viewing and Control of Alternative Scenarios. *ACM Trans. Comput.-Hum. Interact.* 14, 4, Article 17 (jan 2008), 44 pages. https://doi.org/10.1145/1314683.1314685

[26] 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

[27] Lars Nielsen. 2022. An advanced guide to writing prompts for Midjourney (text-to-image). *MLearning.ai* (Sep 2022). https://medium.com/mlearning-ai/an-advanced-guide-to-writing-prompts-for-midjourney-text-to-image-aa12a1e33b6 Accessed: 2023-09-15.

[28] Guy Parsons. 2022. *The DALL·E 2 Prompt Book*. https://dallery.gallery/the-dalle-2-prompt-book/

[29] pharmapsychotic. 2023. CLIP Interrogator: A prompt engineering tool for text-to-image models. https://github.com/pharmapsychotic/clip-interrogator Accessed: 2023-09-15.

[30] Peter Pirolli and Stuart Card. 1999. Information foraging. *Psychological review* 106, 4 (1999), 643.

[31] Peter Pirolli and Stuart Card. 2005. The sensemaking process and leverage points for analyst technology as identified through cognitive task analysis. In *Proceedings of international conference on intelligence analysis*, Vol. 5. McLean, VA, USA, 2–4.

[32] proxima centauri b, surea.i, Stephen Young, and Encyclopedia Erratica. 2023. *Image Synthesis Style Studies Database by parrotzone.art*. https://web.archive.org/web/20230325013519/https://docs.google.com/spreadsheets/d/14xTqtuV3BuKDNhLotB_d1aFlBGnDJOY0BRXJ8-86GpA/edit#gid=0

[33] Aditya Ramesh, Prafulla Dhariwal, Alex Nichol, Casey Chu, and Mark Chen. 2022. Hierarchical Text-Conditional Image Generation with CLIP Latents. arXiv:2204.06125 [cs.CV]

[34] Eric Rawn, Jingyi Li, Eric Paulos, and Sarah Chasins. 2023. Understanding Version Control as Material Interaction with Quickpose. In *Proceedings of the SIGCHI conference on human factors in computing systems*.

[35] Mitchel Resnick, Brad Myers, Kumiyo Nakakoji, Ben Shneiderman, Randy Pausch, Ted Selker, and Mike Eisenberg. 2005. Design Principles for Tools to Support Creative Thinking. (1 2005). https://doi.org/10.1184/R1/6621917.v1

[36] Daniel Ritchie, Ankita Arvind Kejriwal, and Scott R Klemmer. 2011. d. tour: Style-based exploration of design example galleries. In *Proceedings of the 24th annual ACM symposium on User interface software and technology*. 165–174.

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

[38] Daniel M. Russell, Mark J. Stefik, Peter Pirolli, and Stuart K. Card. 1993. The Cost Structure of Sensemaking. In *Proceedings of the INTERACT '93 and CHI '93 Conference on Human Factors in Computing Systems* (Amsterdam, The Netherlands) *(CHI '93)*. Association for Computing Machinery, New York, NY, USA, 269–276. https://doi.org/10.1145/169059.169209

[39] Andy Salerno. 2022. *4.2 Gigabytes, or: How to Draw Anything*. https://andys.page/posts/how-to-draw/

[40] Victor Sanh, Albert Webson, Colin Raffel, Stephen H. Bach, Lintang Sutawika, Zaid Alyafeai, Antoine Chaffin, Arnaud Stiegler, Teven Le Scao, Arun Raja, Manan Dey, M Saiful Bari, Canwen Xu, Urmish Thakker, Shanya Sharma Sharma, Eliza Szczechla, Taewoon Kim, Gunjan Chhablani, Nihal Nayak, Debajyoti Datta, Jonathan Chang, Mike Tian-Jian Jiang, Han Wang, Matteo Manica, Sheng Shen, Zheng Xin Yong, Harshit Pandey, Rachel Bawden, Thomas Wang, Trishala Neeraj, Jos Rozen, Abheesht Sharma, Andrea Santilli, Thibault Fevry, Jason Alan Fries, Ryan Teehan, Tali Bers, Stella Biderman, Leo Gao, Thomas Wolf, and Alexander M. Rush. 2021. Multitask Prompted Training Enables Zero-Shot Task Generalization. https://doi.org/10.48550/ARXIV.2110.08207

[41] Ben Shneiderman. 2002. Creativity Support Tools. *Commun. ACM* 45, 10 (oct 2002), 116–120. https://doi.org/10.1145/570907.570945

[42] Sangho Suh, Bryan Min, Srishti Palani, and Haijun Xia. 2023. Sensecape: Enabling Multilevel Exploration and Sensemaking with Large Language Models. *arXiv preprint arXiv:2305.11483* (2023).

[43] Jerry O. Talton, Daniel Gibson, Lingfeng Yang, Pat Hanrahan, and Vladlen Koltun. 2009. Exploratory Modeling with Collaborative Design Spaces. In *ACM SIGGRAPH Asia 2009 Papers* (Yokohama, Japan) *(SIGGRAPH Asia '09)*. Association for Computing Machinery, New York, NY, USA, Article 167, 10 pages. https://doi.org/10.1145/1661412.1618513

[44] Edward R Tufte. 1993. *Envisioning information*. Vol. 199. Graphics Press Cheshire, CT.

[45] Robert F. Woodbury and Andrew L. Burrow. 2006. A typology of design space explorers. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing* 20, 2 (2006), 143–153. https://doi.org/10.1017/S0890060406060136

[46] Stephen Young. 2022. COG Prompt Parrot. https://github.com/kyrick/cog-prompt-parrot

[47] 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* (Seoul, Republic of Korea) *(CHI '15)*. Association for Computing Machinery, New York, NY, USA, 1201–1210. https://doi.org/10.1145/2702123.2702398

[48] JD Zamfirescu-Pereira, Heather Wei, Amy Xiao, Kitty Gu, Grace Jung, Matthew G Lee, Bjoern Hartmann, and Qian Yang. 2023. Herding AI Cats: Lessons from Designing a Chatbot by Prompting GPT-3. (2023).

[49] J.D. Zamfirescu-Pereira, Richmond 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)*.

[50] Lvmin Zhang and Maneesh Agrawala. 2023. Adding conditional control to text-to-image diffusion models. *arXiv preprint arXiv:2302.05543* (2023).

[51] Jiawei Zhou, Yixuan Zhang, Qianni Luo, Andrea G Parker, and Munmun De Choudhury. 2023. Synthetic Lies: Understanding AI-Generated Misinformation and Evaluating Algorithmic and Human Solutions. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (Hamburg, Germany) *(CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 436, 20 pages. https://doi.org/10.1145/3544548.3581318