Assessing the Potential of Generative AI Models as Participatory Design Tools

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INTRODUCTION

Energy demand around the world is increasing rapidly and continuously. In recent years, factors such as extreme temperatures, the electrification of transportation, and the expansion of data centers have led to a rapid growth in energy demand [1]. In light of these burgeoning energy needs, there is a growing urgency to shift energy generation away from fossil fuels toward clean and reliable sources, in order to address both environmental concerns and long-term sustainability [2]. However, although essential for reducing carbon emissions, the energy transition also raises justice and equity questions, as the benefits and burdens of a transition may affect populations unevenly [3].

Participatory design has been increasingly used to bring in a broader range of perspectives into the development of public infrastructure, including energy systems [4]. As a user-centered research and design approach, it invites end users or those directly affected by technological innovation to actively contribute as co-designers, in the design processes [5,6]. By involving communities, participatory design helps ensure that the outcomes reflect people's needs and preferences, facilitating a smoother transition towards new energy infrastructure.

However, participatory design practices have their own challenges. One of the major difficulties is establishing a shared, neutral language that enables clear and meaningful communication between designers and non-designers. Another challenge is sustaining meaningful collaboration with stakeholders throughout an iterative process. As a project progresses, particularly in later stages, it becomes harder for participants to engage critically with finished-looking prototypes, which lack flexibility of interpretation and box the design to predisposed design decisions or conceptualizations [6]. A third identified challenge is the difficulty participatory design approaches face in identifying all relevant stakeholders or predicting how a technology will be appropriated after deployment [7]. This limitation can narrow the range of perspectives that shape the outcomes of participatory design processes.

Participatory design has recently seen some use of Artificial Intelligence (AI) image generation tools [8]. These tools provide a fast and accessible way to translate ideas into visual representations, and have the potential to address some of the long-standing challenges in participatory design. They can do so by facilitating communication [9], supporting rapid iteration due to their ease and speed of use [10], and allowing users to explore and visualize potential uses and modifications beyond the original design intention [9,11].

To achieve this potential, it becomes essential to investigate how generative AI tools interpret and visually represent the users' intentions. To this end, our study explores how text-to-image generation tools visually respond to user-provided prompts in the context of energy systems design, and reflects on their potential integration in participatory design frameworks as a rapid, and accessible prototyping method. Through a series of design experiments conducted by students in an introductory engineering course, we explore:

1. How different types of energy generation are represented in AI generated images,
2. How accurately the images reflect the users' intended ideas and meet their expectations, and
3. What visual characteristics emerge across generated outputs.

While a comprehensive publication is underway, in this summary paper, we focus solely on the second point: How accurately are the generated images to reflect the user's intended ideas and how well do they meet the user's expectations?

Our results showed that even when most images were aligned with the users' prompts, 46% of the images did not meet their expectations, likely due to limited prompting skills, and the depiction of stereotypical visuals. Still, our findings also suggest that even inaccurate images can help users explore new ideas, imagine alternative futures, and move beyond original design intentions.

The role of prototyping

Prototypes are an invaluable part of design practices. In the initial stages of participatory design, the focus is to explore the users' environment and context, with the main goal to understand the end user's values and priorities, as well as mutually agree on a desired outcome for the technology in question. After a shared understanding of the individuals and their environment is reached, a prototyping stage follows [6,12].

Prototypes are a "physical or digital embodiment of critical elements of the intended design, and an iterative tool to enhance communication, enable learning, and inform decision-making at any point in the design process. Prototyping is the process of creating the physical or digital embodiment of critical elements of the intended design." [13] For an energy system, critical design elements may be specific equipment, infrastructure such as administrative buildings, housing or roads, transmission lines, load centers, etc.

In this work, we explore AI image generation as a prototyping tool to facilitate communication between designers and non-designers, support iteration and continuous learning, and allow users to express and envision future implementation.

METHODOLOGY

During the Fall 2024, an activity relating energy types and AI image generators was assigned to first-year undergraduate engineering students at the University of Michigan. The class followed a design-build-test structure, with a final project to design a hypothetical fission energy facility in collaboration with community members from the region. The students and community members made use of AI image generation to visualize their unique design concepts. The goal of the AI image generation assignment was to test the capacity of text-to-image AI generators to depict a variety of energy systems, looking for accuracy, creativity, and variety across prompts and energy system types. Through this audit of AI image generators, we intended to prepare students to use the image generators during design workshops with community participants.

Students were asked to textually describe an energy facility they wished to visualize, to hand draw a sketch of that facility, and then prompt an AI image generator with their design idea, using the textual description they had developed. For the energy facility being designed, the students could choose to create a facility using wind, solar, hydropower, nuclear fission, nuclear fusion, coal, gas, or a mix of different energy technology types. Students were tasked to generate up to 5 images with flexibility to choose between using the same prompt to generate multiple images with different AI image generators, or using the same image generator with distinct prompts. After the generation of each image, students were asked to answer a set of questions to reflect on their satisfaction with the generated image.

A total of 42 students completed the assignment, which resulted in a collection of 191 experiments, each of which consists of a unique AI-generated image accompanied by a draft sketch of the user's design and the corresponding reflection questions. These experiments make up the data analyzed in our study. The students who performed one or several (up to five) experiments are referred to as the 'users' of the AI image generator.

Students were given complete liberty to choose between AI image generators available online. As a consequence, we found an unequal distribution of AI image generators implemented. We identified 13 unique AI image generators. The biggest representation of an AI image generator in our data corresponds to Dalle-E (or Chatgpt), used in the generation of 36% of the experiments. It is followed by Canva with 17.7% representation, together accounting for little over half of the studied sample. Other AI image generators included: Midjourney, Deep AI, Freepik, Gemini, Open Art, among others.

A team of four researcher assistants (including the first author of this paper) manually made annotations on the collected data by answering specific questions based on all of the elements provided by the users (prompt, draft, generated image, and reflection), aiming to produce a thoughtful interpretation of the user's experience. Annotations addressed the accuracy of the energy type in the images; the realism of the elements and the scene described by the user and depicted by the image generator; the main visual elements of the representations; and the missing or added elements to the image. In this paper we present the user's expectation and accuracy of the image with respect to its prompt.

Energy type annotations included any type of electrical energy generation technology prompted by the user. Given that users were in the process of learning about nuclear technologies, nuclear energy annotations were further differentiated as nuclear fission and nuclear fusion. Furthermore, a distinction between these technologies becomes relevant given that, currently, fission is the only viable nuclear technology for electricity generation. At the risk of being redundant, but to capture instances when users did not explicitly specify the nuclear technology type, a third annotation 'nuclear (doesn't specify)' was introduced. This category could seem redundant, however, considering recent efforts to develop and promote fusion energy along with the introduction of Generation IV fission reactors, we were particularly interested in observing how AI image generators interpret nuclear energy prompts when no specific type was mentioned.

Following the four independent annotations, a majority vote process was used to determine the final annotations for each experiment. In cases where no majority was reached, the first author's annotation was prioritized, given her greater proficiency in the energy technologies compared with the rest of the student annotators.

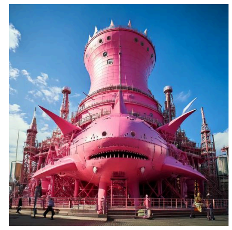
RESULTS

The section below shows initial results related to AI image accuracy, prompts, and user expectations.

Accuracy of image depiction and user expectation

To determine if a user's expectation was fulfilled, we inspected how similar the generated images were to what the user had envisioned. Researchers examined the reflection questions answered by the students, as well as the hand-drawn draft, to get a better idea of what the user

Table 1. Examples of users' expectations for the generated images

How similar is the image to the user's expectation:	Very similar (54%)	Similar but has different elements (25%)	Gets the idea but has a different representation (11.5%)	Completely different (8.4%)
Example of generated image				
User's comments of the example image	"The brick houses are exactly what I had in mind as well as the nuclear reactor as well."	"[...] it did set the drawing in a city like I said but it sort of just sprinkled random cooling towers all over the place. [...]"	"[...] the AI generator made it better than what I thought it was going to be. It made the whole thing into a shark instead of just making it with a theme of sharks."	"This image does not match my prompt at all, I think that the AI either did not comprehend what I had said or just didn't know what to create."

intended or the impression they got. Table 1 shows examples of the user's comments, which reflect their expectation fulfillment. We found that about half of the time (54.5%) the generated images were very similar to what the user expected. Only 8.4% of the images presented something completely different, and the remainder of the time, the image conveyed something somewhat similar, either by containing different elements (25.7%) or a different representation (11.5%).

To better understand the alignment between the generated images and users' expectations, we compared the accuracy of the images with respect to (w.r.t.) their written prompts versus the users' expectations of the images (Fig. 1). Although these two measures (image accuracy and user expectation) might seem to yield the same results, we found that the resemblance of the image to its prompt did not necessarily reflect how well the image fulfilled the user's expectations. We believe that some of the mismatch between the images and the user's expectations may be due to vague or poorly phrased prompts. For instance, even if an image matches the elements described in the prompt (from the researcher's perspective), it may not fully align with the user's envisioned outcome (interpreted from their reflections and hand-drawn drafts). Since this study did not directly examine prompt phrasing, further investigation is needed to better understand its role in shaping generative AI outputs, as well as the degree to which users' domain expertise in prompt creation affects designer-user engagement in design workshops.

Our findings suggest that the more closely an image aligns with the elements described in the prompt, the higher the likelihood it will meet the user's expectations. Interestingly, images that captured the general idea of the prompt but included different elements did not meet the users' expectations at all. This result indicates that even though the overall concept might be understood, the specific details matter greatly in fulfilling the user's expectations. On the other hand, images with completely different elements still met the user's expectations in one instance. Although this was the exception rather than the norm, it suggests what Guridi et al. referred to as "conversational imperfects", imperfect depictions of the user's ideas that can spark inspiration and foster exploration of different approaches in the design process [11].

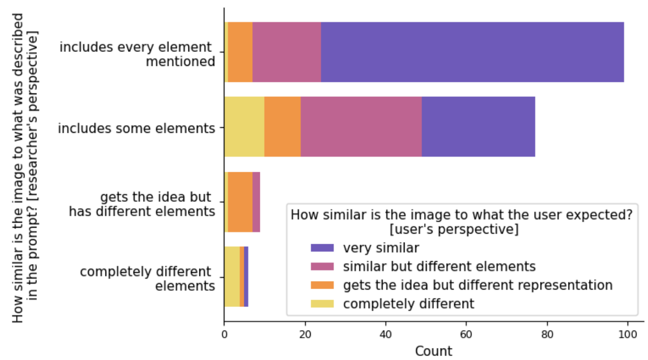


Fig. 1. Accuracy of depicted image (w.r.t its prompt) vs user expectation.

In Fig.2. we explored the same comparison, broken down by energy types. We found images depicting fusion technology were the least accurate compared to their prompts. This result is likely influenced by the early development state of fusion technology, and the lack of operational power plants. Furthermore, images depicting nuclear technologies, whether unspecified, fission or fusion, met users' expectations the least. This may be due to generative AI models' tendency to over-represent stereotypical features, such as cooling towers, as the main representation of nuclear technologies [14]. As new reactor designs emerge and fusion developments advances, traditional imagery may become too limited to capture the evolving vision users might have for these technologies.

In the design process, prototypes can serve as valuable tools to visualize, understand, and discuss how critical elements of an energy system can be meaningfully integrated into host communities. As we explore the generated images in our study, we begin to conceptualize

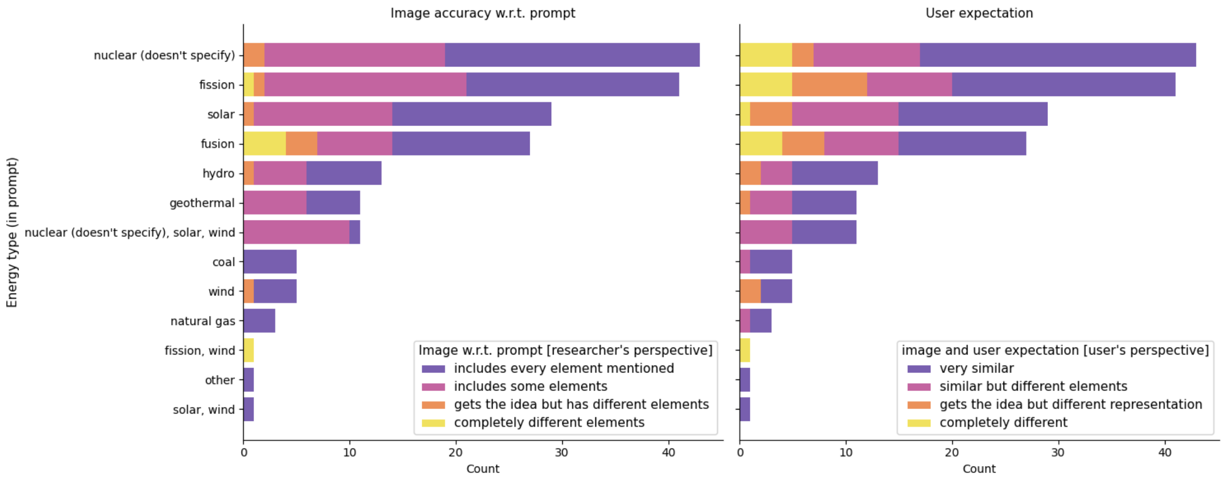


Fig.2. Accuracy of depicted image (w.r.t its prompt) & user's expectation vs energy type

the role that generative AI models can play in participatory design practices.

In a forthcoming, longer article, we will address the distinct energy types in generated images, as well as the visual characteristics that emerged across outputs. We will further discuss the relevance, opportunities and concerns surrounding the adoption of AI tools in the co-design of energy systems.

REFERENCES

1. IEA, "Global Energy Review 2025," IEA, Paris (2025).
2. K. CALVIN et al., "IPCC, 2023: Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (eds.)]. IPCC, Geneva, Switzerland.," Intergovernmental Panel on Climate Change (IPCC) (2023); https://doi.org/10.59327/IPCC/AR6-9789291691647.
3. S. CARLEY and D. M. KONISKY, "The justice and equity implications of the clean energy transition," Nat. Energy **5** 8, 569, Nature Publishing Group (2020); https://doi.org/10.1038/s41560-020-0641-6.
4. R. SHELBY, Y. PEREZ, and A. AGOGINO, "Co-Design Methodology for the Development of Sustainable and Renewable Energy Systems for Underserved Communities: A Case Study With the Pinoleville Pomo Nation," in Volume 9: 23rd International Conference on Design Theory and Methodology; 16th Design for Manufacturing and the Life Cycle Conference, pp. 515–526, ASMEDC, Washington, DC, USA (2011); https://doi.org/10.1115/DETC2011-47748.
5. P. WACNIK, S. DALY, and A. VERMA, "Participatory design: A systematic review and insights for future practice," arXiv (2024); https://doi.org/10.48550/ARXIV.2409.17952.
6. C. SPINUZZI, "The Methodology of Participatory Design," 2, Tech. Commun. **52** 2, 163 (2005).
7. E. BJÖGVINSSON, P. EHN, and P.-A. HILLGREN, "Design Things and Design Thinking: Contemporary Participatory Design Challenges," Des. Issues **28** 3, 101 (2012); https://doi.org/10.1162/DESI_a_00165.
8. L.-Y. CHIOU et al., "Designing with AI: An Exploration of Co-Ideation with Image Generators," in Proceedings of the 2023 ACM Designing Interactive Systems Conference, pp. 1941–1954, ACM, Pittsburgh PA USA (2023); https://doi.org/10.1145/3563657.3596001.
9. J. A. GURIDI et al., "Image Generative AI to Design Public Spaces: a Reflection of How AI Could Improve Co-Design of Public Parks," Digit Gov Res Pr. **6** 1, 7:1 (2025); https://doi.org/10.1145/3656588.
10. S. KRISHNAKUMAR et al., "Make it or draw it? Investigating the communicative trade-offs between sketches and prototypes," Des. Sci. **9**, e32 (2023); https://doi.org/10.1017/dsj.2023.31.
11. J. A. GURIDI et al., "From Fake Perfects to Conversational Imperfects: Exploring Image-Generative AI as a Boundary Object for Participatory Design of Public Spaces" (2024); https://doi.org/10.1145/3710912.
12. S. BØDKER et al., *Participatory Design*, Springer International Publishing, Cham (2022); https://doi.org/10.1007/978-3-031-02235-7.
13. C. A. LAUFF, D. KOTYS-SCHWARTZ, and M. E. RENTSCHLER, "What is a Prototype? What are the Roles of Prototypes in Companies?," J. Mech. Des. **140** 6, 061102 (2018); https://doi.org/10.1115/1.4039340.
14. V. JOYNT et al., "A comparative analysis of text-to-image generative AI models in scientific contexts: a case study on nuclear power," 1, Sci. Rep. **14** 1, 30377 (2024); https://doi.org/10.1038/s41598-024-79705-4.