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Research Note

Generative AI text-to-image for community participation in landscape planning

Ishraq Awashra [a,*], Aaron W. Thompson [a], Kristin Floress [b], J.Gordon Arbuckle [c], Sarah P. Church [d], Ken Genskow [e], Linda S. Prokopy [f], Yichao Rui [g], Omar Tesdell [h]

[a] Purdue University, Department of Horticulture and Landscape Architecture, 625 Agriculture Mall Dr, West Lafayette, IN 47907, United States
[b] Research Social Scientist, USDA Forest Service Northern Research Station, Evanston, IL 60201, United States
[c] Iowa State University, Department of Sociology and Criminal Justice, 510 Farm House Ln, Ames, IA 50011-1054, United States
[d] Montana State University, Department of Earth Sciences, 226 Traphagen Hall, Bozeman, MT 59717, United States
[e] University of Wisconsin-Madison, Department of Planning and Landscape Architecture, 925 Bascom Mall, Madison, WI 53706, United States
[f] University of Vermont, Office of the Dean, Morrill Hall, 146 University Place, Burlington, VT 05405, United States
[g] Purdue University, Department of Agronomy, 915 W State St, West Lafayette, IN 47907, United States
[h] Birzeit University, Department of Geography, Al - Marj St, Birzeit 627, Palestine

HIGHLIGHTS

- Generative AI text-to-image tools are increasingly used for community engagement.
- We propose a new approach of integrating generative AI text-to-image tools in the process of participatory design.
- We compromise the pace of translating participatory discussions into images, balancing between real-time approaches and extended periods.
- This approach involves using 'controlled imperfect' generative images.
- We collect keywords during the participatory discussions for prompt crafting, streamlining the translation of the discussions into visuals.

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ABSTRACT

Effective landscape planning relies on community insights through participatory design to achieve local needs. Visual media can assist community engagement, and visuals created using generative AI text-to-image models are increasingly adopted for such purposes. We explore a new approach of including generative images in participatory planning through a case study with the Diverse Corn Belt Project in the US Corn Belt. Our method is applicable to other contexts, and adds to the literature in three ways. First, we propose a compromise between real-time image generation and extended time workflows of translating participatory discussions into generative images, benefiting from the instant generation of generative models while controlling the output. Building on this proposed pace, we suggest creating what we call 'controlled imperfect' images as a balance between "fake perfects" and "conversational imperfects" suggested by the literature. In addition, we propose simplifying the process of translating participatory discussions into an image output through directly collecting keywords necessary for prompt engineering. We build on our case study to outline a revised method for future research.

1. Introduction

Landscape planning is a design approach based on a shared understanding of a specific geographic region's social, ecological, and economic conditions to propose sustainable future land uses, accounting for multiple factors integrating ecosystems, landforms, water resources, and human activities. This process requires interdisciplinary knowledge and experience to identify trends, goals, and objectives affecting future

* Corresponding author.
E-mail addresses: iawashra@purdue.edu (I. Awashra), awthomps@purdue.edu (A.W. Thompson), kristin.m.floress@usda.gov (K. Floress), arbuckle@iastate.edu (J.Gordon Arbuckle), sarah.church@montana.edu (S.P. Church), kgenskow@wisc.edu (K. Genskow), linda.prokopy@uvm.edu (L.S. Prokopy), ruiy@purdue.edu (Y. Rui), otesdell@birzeit.edu (O. Tesdell).

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land use possibilities (Filor, 1994; Gazvoda, 2002; Seddon, 1986). Building on this foundation, participatory design has emerged as a crucial approach, recognizing that local communities who live and work in the landscape possess valuable place-based knowledge essential for identifying sustainable landscape solutions (Filor, 1994; Hester, 2012; Sanoff, 2016; Sanoff, 2000). Facilitating effective community engagement is key to this process, and visualization tools have been shown to be effective in this regard (e.g., Al-Kodmany, 2010; Al-Kodmany, 2020; Fredericks et al., 2018; Kajosaari et al., 2024; Lovett et al., 2015; Senbel & Church, 2011).

As generative text-to-image visualization tools gain momentum in designing the environment (e.g., Fernberg, 2024; Fernberg & Chamberlain; 2024; Li & Amoroso, 2023; Schlickman et al., 2024), some researchers are also exploring the potential of these tools in the participatory design process (e.g., Bova, 2025; Guridi, Hwang, et al., 2025). While visual methods prove effective for working with communities on design projects, common tools (e.g., photographs, maps, and physical models) often require significant amounts of time between iterations and can limit the interactivity needed for effective community collaboration (Al-Kodmany, 2010; Sanoff, 2026; Sanoff, 2000). Ideally, designers could quickly update designs based on community feedback. As generative AI text-to-image tools can rapidly turn texts into images, such tools may offer a solution to this challenge (e.g., Bova, 2025). Despite the availability and promise of technology to do so, generating images that reflect text prompts requires skills and training in prompt engineering and image curation, especially as the generative models may yield unexpected results that designers need to navigate (Guridi, Hwang, et al., 2025). Further, images generated instantly using a one-shot approach can create "fake perfects", which can limit conversation because of the perception of perfection and suggests the need for "conversational imperfects" (Guridi, Cheyre, et al. 2025). On the other hand, "conversational imperfects" generated using a one-shot approach might not be always appropriate for the specific participatory discussion. As a result, designers must critically approach using generative AI images in participatory settings and develop methods to "navigate the unexpected" outputs and avoid potential harm to participants, such as when the results are biased or offensive (Guridi, Cheyre, et al., 2025). In addition, the process of translating participatory text data (usually in the form of text transcripts) to an image output is a long process, making the creation of proper images from the participatory discussions a long process, even when the generative text-to-image can be produced rapidly (Alkhateeb et al., 2024; Guridi, Cheyre, et al., 2025; Konarieva et al., 2019).

In light of this, we introduce a replicable approach that integrates generative AI text-to-image tools into the participatory design process. Designers can apply this methodology to various contexts, and we illustrate its potential through a case study of the Diverse Corn Belt (DCB) project. Through our approach, we contribute to the literature in three ways. First, we suggest a compromise between real-time image generation methods, where participants see the entire text-to-image process as part of the participatory process (e.g., Bova, 2025; Guridi, Hwang, et al., 2025), and the extended time periods between iterations when using the generative tools in a traditional pace that ignores their potential for instant generation (e.g., Alkhateeb et al., 2024). This approach ensures that the images used in the participatory setting are appropriate for the specific participatory discussion. The generation of instant images using a one-shot approach might be unpredictable, leading to "fake perfect" images that limit discussion as they are seen as complete or uneditable (Guridi, Hwang, et al., 2025). While "imperfect" generative images are favored over "fake perfects" as they potentially allow for more conversation (Guridi, Hwang, et al., 2025), the imperfection of instant generation can be risky (Wasielewski, 2023), potentially leading community conversations in unwanted directions. We contribute to the discussion of "fake perfects" and "conversational imperfects" in the literature by introducing the use of what we call 'controlled imperfects.' Further, we present a process that simplifies the conversion of participatory big-text data (e.g., transcripts) into images, which is typically a long and intensive process. Notably, we skip the "text compression" phase of participatory data analysis (Konarieva et al., 2019), accelerating the generative process.

Below, we present related work in this burgeoning field (Section 2), followed by the case study context within which we developed our method (Section 3). We present the text-to-image methods we used in our case (Section 4), the results thereof (Section 5), and a discussion of selected aspects of our case and results (Section 6). Building on our case results, we then propose a revised process to be used and tested in future work focused on integrating generative AI text-to-image into participatory design processes (Section 7). Finally, we present some of the limitations of our research (Section 8).

2. Related work

Designers in disciplines focused on the physical environment are increasingly adopting AI tools (e.g., Hakimshafaei, 2023; Phillips et al., 2024). Generative AI has also been incorporated into the design toolkit of landscape architects (Fernberg, 2024; Fernberg & Chamberlain; 2024; Xing et al., 2025). Designers use generative AI tools to: create early-stage architectural drawings for interior and exterior design (Ploennigs & Berger, 2023), generate and evaluate landscape design proposals (Lee, 2025), create floor plans and 3D models from sketches (Li et al., 2024), generate design options for urban areas (Schlickman & Magana-Leon, 2024), design small scale garden layouts (Senem et al., 2024), generate landscape renderings (Huang et al., 2024; Li & Amoroso, 2023), and create asset libraries of rendering elements (Fernberg et al., 2023).

Generative AI tools are increasingly being integrated into community engagement processes (e.g., Du et al., 2024; Guridi, Cheyre, et al., 2025), although this application remains limited (Guridi, Hwang, et al., 2025; Valença et al., 2025). One consideration is the basic usefulness of this approach. For example, Schlickman et al. (2024) tested whether community participants could distinguish previously made generative AI images from other selected media, finding that people often could not tell the difference. Bova (2025) explored integrating generative AI text-to-image tools into urban regeneration using World Café workshops for two sites in Italy, creating images from textual proposals developed in the workshop and prompt crafting in real-time. As much as this research is promising, there are few limitations as the generated images lacked realism. Moreover, real-time image generation with participants can be problematic, as the results of generative AI text-to-image tools cannot be fully anticipated as Wasielewski (2023) suggested. Also, hampering the image generation process is an incomplete understanding of the participatory proposals, leading to a poor connection between the community needs and the prompt (Bova, 2025).

Others have worked closely with individuals to gather information about the thoughts that informed image generation. Alkhateeb et al. (2024) interviewed displaced Syrian refugees to capture their personal stories about their urban landscapes, using narratives to inform prompts for text-to-image generation of the landscapes. They then shared the resulting images with interviewees for evaluation. While this method is innovative and likely meaningful to interviewees, its transferability to participatory community design is limited. First, the approach relies on individual responses and experiences, whereas participatory design typically involves collaborative discussions and decision-making. Second, the researchers shared images with participants without further editing or control of the instant text-to-image result, which may be problematic given the topic's sensitive nature. As Alkhateeb et al. (2024) did, Guridi, Hwang, et al. (2025) used interviews to create generative visuals, but through real-time interviews with community members to develop designs of public urban space. These generative AI-mediated interviews allowed for instant modifications of the visuals, but the researchers reported critical considerations, including managing unexpected visual outputs generated in a real-time setting. Importantly, Guridi, Hwang, et al. (2025) found that "conversational imperfect" images were better for sparking discussions compared to "fake perfects," about which participants had few suggestions to change.

As illustrated above, there is a need for more qualitative information about participants' thought processes related to images generated by AI through text prompts and with further testing of generative AI's utility in participatory processes. Our paper answers the call Schlickman et al. (2024) and Guridi, Cheyre, et al. (2025) made for generative AI tools to be tested and reflected upon by designers. We also analyze participant discussions around the images, a need identified by others (Bova, 2025; Schlickman et al., 2024).

3. Study context

Our method was developed for and tested in facilitated community visioning sessions for sustainable agricultural landscapes in the Corn Belt. This is a region where a large-scale industrialized monoculture of corn and soybean dominates the rural landscapes of the Midwestern United States (Prokopy, Carlson et al., 2020; Prokopy, Gramig et al., 2020). This landscape of intensive monocropping leads to negative environmental, social, and economic impacts (Jackson & Jackson, 2002; Jackson, 2008; Prokopy, Gramig, et al., 2020). The Diverse Corn Belt (DCB) Project is a USDA-funded project that aims to, among other goals, co-produce landscape-level scenarios supported by diversified agriculture in the US Midwest (Asproth et al., 2025; Prokopy, Carlson, et al., 2020; Traldi et al., 2024). To accomplish this, Reimagining Agricultural Diversity (RAD) teams were formed in each of three states (Illinois, Indiana, and Iowa) that include farmers, landowners, producers, researchers, community members, food processors, and retailers were developed. Potential RAD team participants in each state were identified through direct contacts research team members had in their extensive networks within each state and then by asking those initial contacts to share the invitation with others they felt might be interested. A sub-team of planners, social scientists, and landscape architects from the DCB project leads in-depth visioning sessions with each state's RAD team to create collectively owned visions of Midwestern diversified agricultural landscapes. We tested our generative text-to-image for participatory design methodology in one set of RAD visioning sessions (i.e., one session in each of the three states). Activities were approved through the Purdue University Institutional Research Board (Protocol #2022-151).

4. Research methods

We used a process similar to others' methods using generative AI text-to-image for participatory design processes, whereby we went through a tool selection process (Step 1), generated *a priori* images for the sessions (Step 2), and used the images as the basis for discussion during sessions (Step 3). We also used participant input (Step 4) to revise images (Step 5), but this process differed between sessions and from previous approaches. Based on our experiences in the first two workshops, we revised parts of our process for the third (Steps 4 and 5), as shown in Fig. 1.

4.1. Selecting AI text-to-image tool (Step 1)

Because there are many generative text-to-image tools, we first reviewed three popular tools to select the most suitable for our research. We tested DALL.E 2, Midjourney, and Adobe Firefly, as these models were promoted as having potential for design applications and were available to us from the initial stages of our research (e.g., Fernberg et al., 2023; Ploennigs & Berger, 2023; Phillips et al., 2024). We tested each for its capability to represent agricultural landscapes. We followed what others have suggested for evaluating generative AI text-to-image tools by using the same prompt as an input in different generative tools (e.g., Li et al., 2023; Wang et al., 2023). We ran ten landscape-related prompts in each of the three selected tools. We selected Midjourney because it has better overall landscape representation quality, fewer representation flaws in a landscape setting, and better prompt-

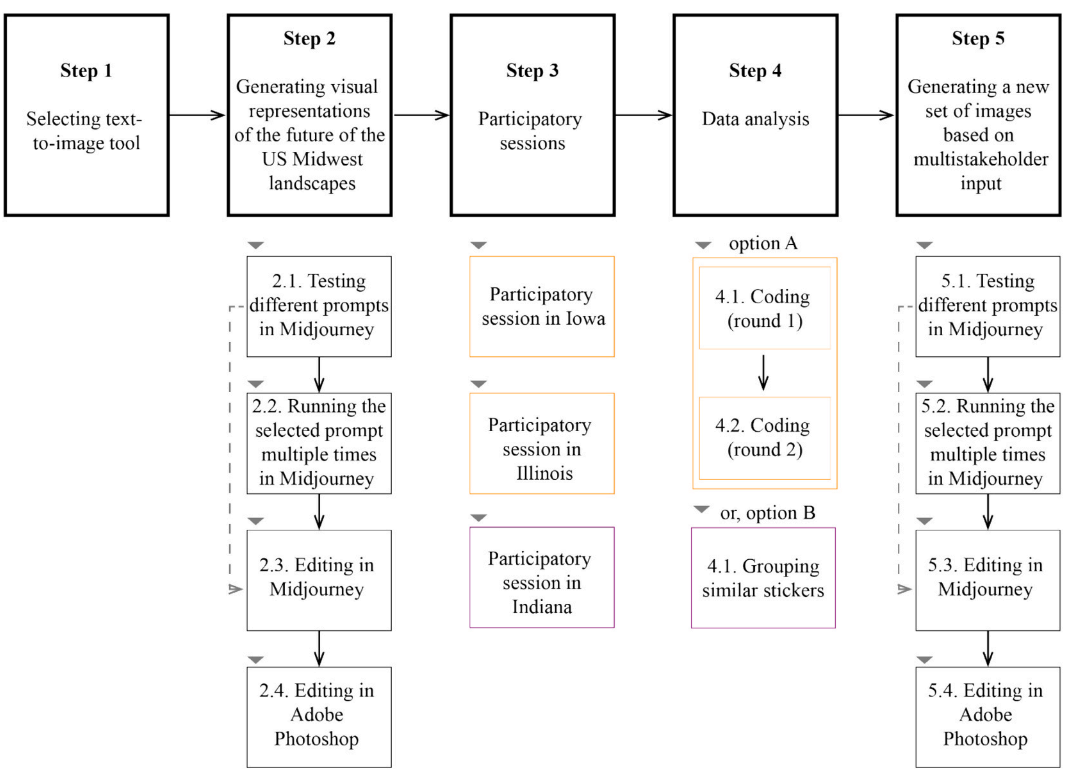

Fig. 1. The different steps of our research method. The orange boxes represent the steps we followed as we worked with Illinois and Iowa community, while the purple boxes represent the Indiana meeting. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

following abilities than DALL.E 2 and Adobe Firefly (see Appendix A). While we did not follow a pre-established evaluation approach of generative text-to-image tools, such as the one established by Li et al., (2023), we believe that Midjourney was the best for our research needs. We recommend other researchers follow a more rigorous tool evaluation and quality assessment to select a generative AI tool for their research before moving to the next step of our proposed method (e.g., Li et al., 2023; Wang et al., 2023).

4.2. Generating visuals of the future of the US corn belt landscapes (Step 2)

We prepared generative text-to-image conceptual visuals of five initial diversification agricultural systems as defined by the DCB project, recognizing that different systems and definitions would likely result from project activities. The DCB diversified agricultural systems were developed for the Midwestern US context as they can support environmental, social, and economic outcomes in this region (Asprooth et al. 2025). The five systems are (1) extended rotation with three or more crops over 3+ years, (2) perennial pasture/forage and perennial bioenergy crops, (3) horticultural food crops, (4) integrated/grazed livestock, and (5) agroforestry (please see Appendix B for the definitions of the systems, and Appendix I for the generative images we created for the five systems). Here, we focus on the agroforestry system as an example to showcase the steps we followed in our method. The following steps show that generating images with AI text-to-image tools is an iterative process, requires a continuous evaluation of each result before moving to the next step, and that "post-processing" using an editing tool is necessary to "fine tune" the final generative output (Liu & Chilton, 2023; Oppenlaender, 2022). Please see the conceptual figure below (Fig. 2).

- **Step 2.1:** We used the DCB definition of agroforestry to guide prompt writing. We tested different prompts in Midjourney V5.2 to evaluate their potential to generate reasonable results for the agroforestry system. Our experimentation with prompting and evaluation of early results led us to craft better prompts to produce better outputs. This process was nonlinear.

Fig. 2. A conceptual drawing of (Step 2). The highlighted parts are the selected parts for each step. From top to bottom: selecting a prompt; selecting an output of one query generated by the selected prompt; out of the four results from the selected query, selecting one result for editing, and then editing it; finally, editing in Photoshop.

- **Step 2.2:** We ran the selected prompt multiple times in Midjourney. Once we had a promising visual result, we treated this visual result as the base for our final output.
- **Step 2.3:** Using various Midjourney editing tools, we edited the base visual result (Purdue CCED, 2024) (see Appendix C for an example). The editing process was also nonlinear and required multiple workflows. We sometimes used new prompts during the editing phase to support image refinement. Hundreds of images were discarded during the process, as shown in Fig. 3 where discarded images from the agroforestry image generation process may be viewed.
- **Step 2.4:** We used Adobe Photoshop for minor editing of the Step 2.3 output. The editing process focused mainly on enlarging property size, removing excess roads, and editing Midjourney flaws that we could not eliminate directly in Midjourney, such as removing some light structures from the Midjourney-generated agroforestry image.

4.3. Participatory sessions (Step 3)

We collaborated with the RAD teams in three DCB visioning workshops, held in Illinois, Iowa, and Indiana during February, March, and August 2024. Around seventy collaborators included farmers, agricultural landowners, agricultural consultants, educators, researchers, nonprofit employees, NGO employees, and government agents. We used the World Café (The World Café Community Foundation, 2015a, 2015b) style activity to engage RAD teams in evaluating five text-to-image representations, one for each of the five diversified agricultural systems, and to gather participants' insights about how they see their future environment. We started our activity with a general introduction about Midjourney and explained that the presented images were not predetermined visions of the future, rather that this is a visual tool to support discussions of potential futures.

Participants were asked to randomly gather around five tables in Illinois and Indiana, and three tables in Iowa. Five researchers facilitated the discussions in each session, focusing on one agricultural system. Each facilitator used one (32*32 in.) printed poster of one of the five AI-generated images to direct the discussions about the agricultural system represented in the image. While participants typically move between tables in a typical World Café setting, in our case facilitators were the "travelers" because of time limitations (The World Café Community Foundation, 2015a, 2015b). Discussions at each table were used to document the process and later transcribed for analysis.

Participants were asked two questions: **(1) What about the pictured system will you KEEP** (What about the pictured system are you excited about or believe will work well in your region?), and **(2) What about the pictured system will you CHANGE** (What about the pictured system will need to be modified for it to work well in your region?). We handed stickers with blue and yellow arrows to the participants (blue for "keep" and yellow for "change"). Participants at each table discussed their thoughts and shared them directly on the poster by writing on the stickers. For each round, the discussions lasted from 7 to 10 min. Once a round was over, the facilitators moved to the next table, summarized the responses of the previous table(s) to the new group, and asked the new group to build on, but not repeat, the work of the previous one(s). The figure below (Fig. 4) shows the posters of agroforestry with input from multiple stakeholders in Illinois, Iowa, and Indiana (please see Appendix D for enlarged versions of the posters).

4.4. Data analysis of Illinois and Iowa meetings (Step 4, option a)

Participants posted 76 notes as responses on the agroforestry posters presented in Illinois and Iowa RAD visioning sessions (Please see Appendix D). These responses were coded to identify unique themes and priorities to craft the new prompts for the agroforestry image (see Step 5 below). We began with a typical basic categorical coding process (Creswell, 2009), but qualitative analysis procedures intended to develop a phenomenological "essence description" or a grounded theory – in other words, a final explanation for phenomena of interest in a given case – were too structured and in-depth to meet the need we had of revising visualizations based on participant feedback. The full initial process, the results of which we largely discarded in favor of the adapted

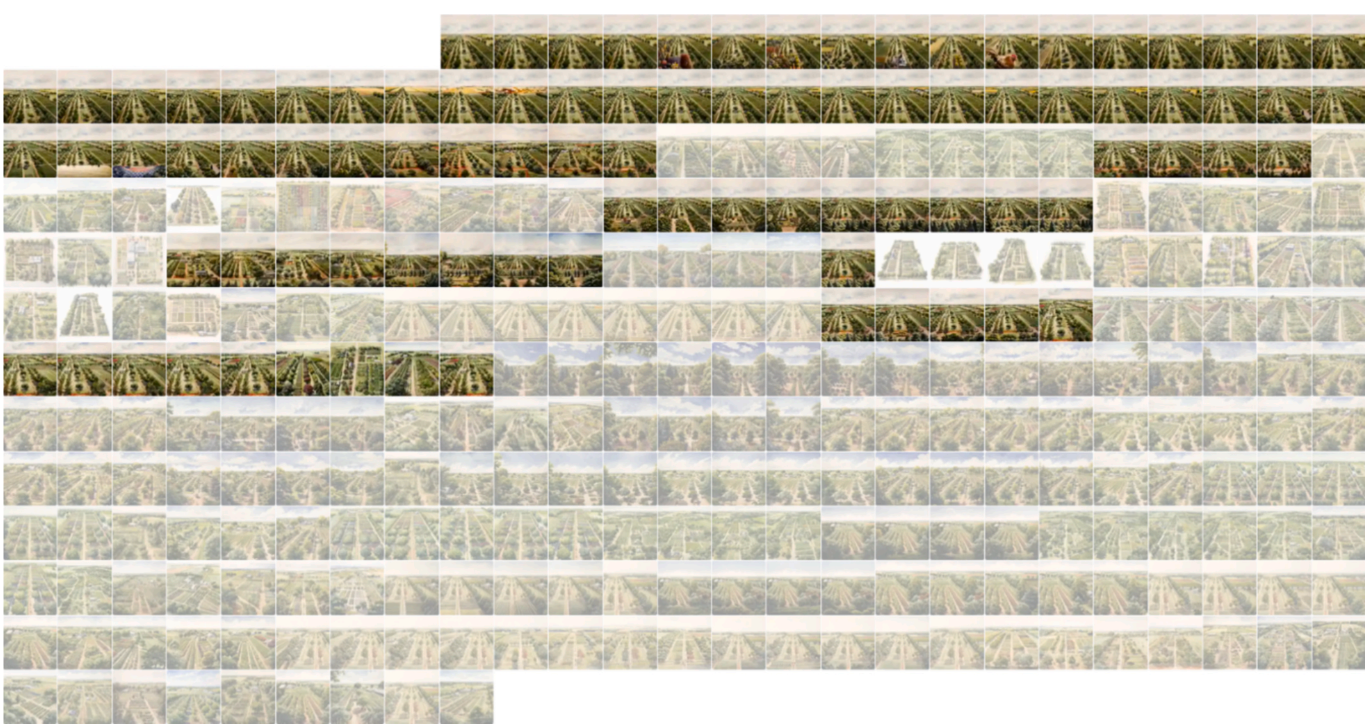

Fig. 3. A screenshot from Midjourney website. The screenshot shows 301 images generated through our experimentations with the agroforestry image (Steps 2.1 – 2.3). The highlighted images are the parts of the workflow that led to the generation of the final image. Other images were only part of the process, but did not lead to the final result.

Fig. 4. Top left: The presented poster for the agroforestry system. Top right and bottom: Agroforestry poster showing participants' responses (Step 3) in Illinois Iowa, and Indiana. Initial image prompt: "Aerial bird view perspective watercolor rendering of a midwestern grid landscape that has largescale alley cropping, with woody perennials and shrubs, with berry shrubs, with grape trees, with apple trees, with nut trees, with herb shrubs."

approach explained below, can be found in Appendix E. Our revised methods are included here.

One researcher used transcripts from visioning sessions and notes from the research team's coding meetings to develop thematic groupings of participants' written responses to images. The transcripts were not analyzed in depth; instead, they were used to determine the context within which people were discussing certain written comments and allowed the researcher to group comments within the correct theme. The result is a final set of twelve themes comprised of information that are used to refine images and one theme capturing conceptual information that could not be used to refine images (e.g., "economic"). The twelve visualizable themes (please see (Fig. 5) below, and Appendix E) include: (1) crop and livestock diversity; (2) ecosystem and natural resources; (3) community; (4) on-farm management practices; (5) infrastructure; (6) farm buildings; (7) storage, processing, and distribution; (8) representation flaws; (9) light structures; (10) renewable energy; (11) market; (12) machine, equipment, tool, and modern technology. All conceptual comments were coded as (13) non-visual, other. Some participant responses to images were categorized under more than one theme, such as "edible windbreaks," which we categorized under both "crop and livestock diversity" and "on-farm management practices" themes. For the agroforestry image, the most common themes were as follows:

- Crop and livestock diversity (24 %)
- Ecosystem and natural resources (18 %)
- Community (9 %)
- Infrastructure (9 %)
- Storage, processing, and distribution (7 %)
- Representation flaws (7 %)

4.5. *Generating new images (Step 5) based on stakeholder responses in Illinois and Iowa*

The responses from participatory sessions (Step 3) in Iowa and Illinois, and the themes identified in Step 4 (option a) allowed us to generate new visuals addressing stakeholders' visions of their landscapes. The workflow below led to the creation of a new set of visuals addressing most of the participants' input. For more information about this step, please see (Appendix F, Appendix J) and [Purdue, 2024].

- **Step 5.1**: Different prompts were tested in Midjourney V6.1 until we achieved an effective prompt that generated the images we expected or hoped for (similar to Step 2.1). The new, reasonably short, prompts were crafted based on the most common themes identified from our analysis (steps 3 and 4) as recommended by others (Alkhateeb et al., 2024; Li et al., 2023). While this approach did not

Fig. 5. Grouping similar sticker responses together based on community engagement sessions in Illinois and Iowa.

incorporate every individual response, it still allowed us to address the priority themes and many aspects of the other themes.

- **Step 5.2:** We again followed the same process as Step 2.2, revising the prompt over multiple iterations until we achieved an appropriate base image.
- **Step 5.3:** We edited the result of Step 5.2 using various Midjourney editing tools. Here, we used new prompts and many reference images for inpainting (drawing over selected parts of the image). The editing focused on refining the images to address stakeholder responses. This process was nonlinear, and around two thousand images were discarded while generating the new agroforestry image (please see Appendix H for a sample of discarded images and the reason behind their exclusion).
- **Step 5.4**: Even after hundreds of attempts, we failed to add accurate representation of humans and animals (Please see a sample in Appendix H) in the image using the Midjourney inpainting tool (vary region). In response, we used Adobe Photoshop to add silhouette cutouts of people, livestock, and birds to the final Midjourney result as these aspects were very important to the community stakeholders.

4.6. Data analysis of Indiana meeting (Step 4, option b)

Our first approach of sticker data analysis (Step 4, option a) took a few hours to conduct and went through multiple rounds over a month. Since we are trying to develop a quick method of data analysis that will lead to a quick image regeneration, we tested a new data analysis approach to support prompt making using data from the Indiana RAD

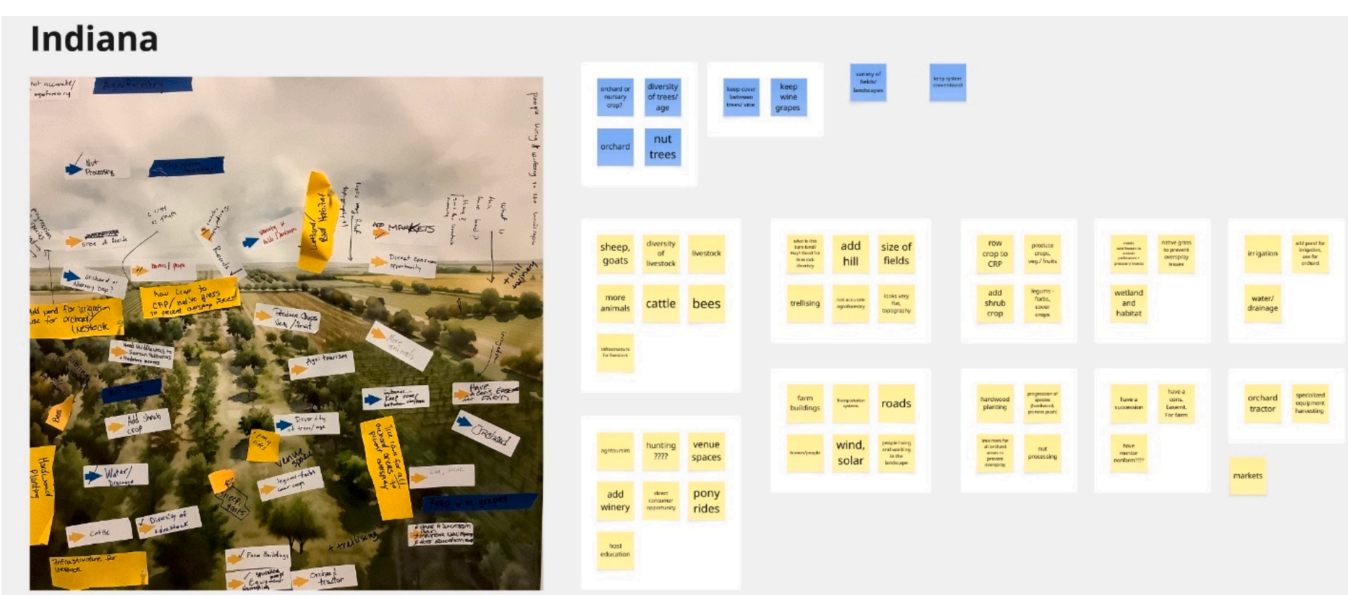

Fig. 6. Grouping similar sticker responses of the Indiana meeting together.

meeting. The Indiana meeting participants posted 54 notes as responses on the agroforestry poster. We created a sticky note for each community response on a Miro Board and distinguished the "keep" responses from the "change" responses (please see the figure below (Fig. 6)). Two researchers grouped similar responses together, and we were able to finish the grouping process and reviewing the groups in less than 10 minutes.

4.7. Generating new images (Step 5) based on stakeholder responses in Indiana

In our previous approach to this step, we did not set a time limit for our experimentations, but here we tried to test if we could create a high-quality updated agroforestry image within a limited time, so we allowed ourselves to spend only one hour on this step. The Indiana responses (from Step 3) that were grouped thematically (Step 4, option b) were used to craft new prompts to generate the new image. We followed the same workflow presented in section 4.5 above. Different prompts we tried in (Step 5.1) included keywords from the largest groups of similar stickers of keep and change. Then, we tried to include other keywords during the editing (inpainting) process.

5. Results

5.1. Insights on community's reaction to the generative AI images (results of Step 2)

The use of generative images in the participatory sessions proved effective, aligning with the literature about visual tools in participatory design (e.g., Guridi, Hwang, et al., 2025; Sanoff, 2000; Valença et al., 2025). For example, a participant thought that having a scenario helps thinking about the future: "*I like the picture… I like that better than just having to think up what you'd add kind of thing. It makes you think a little differently with the picture… I just like having a scenario sort of as the background. Whether it's horticulture, agroforestry…*" While the presented scenarios were not related to a specific site, participants were aware that the idea is to imagine this scenario as their future landscape, so they built their discussions around this assumption. For example, a participant said: *"If that was my orchard, I'd have sheep grazing underneath those trees."*

Regarding the quality of the images, different stakeholders thought that the images were good: *"Yeah, I think it's a good visual."* Also, some participants were impressed that these images were created by a generative AI tool or by the quality of the result: *"I was so impressed by this image, and then I learned that it was AI. I was like, wow, somebody did a lot of work here.*" Another participant said: *"Actually, for an AI bot, this is really good. I mean, my gosh, this is really good."* In addition to the satisfaction with the images, some participants reactions shows that the images were quite realistic: *"I'm just hearing the birds and the insects looking at this."* Eventually, some participants seemed to relate to the presented visions and the possibility to live in such landscapes: *"This does look like a place I'd be more likely to want to live."*

When we created the generative images with Midjourney (Step 2), we tried to make the images as accurate as possible because we aimed to deliver correct representations to the community stakeholders. Despite that, the images were still inaccurate. For instance, an Indiana meeting participant critiques the agroforestry image saying: *"It doesn't look very true agroforestry… I don't think it's accurate…"* However, such inaccuracy led to a valuable discussion, with another participant from the same secession saying: *"Well, it looks green in between. So I'm going to say they have perennial growth underneath, which is good."* The green rendering between the trees, while not specifically representing perennials, allowed us to understand the need for perennials under the trees to make this landscape a more accurate representation of agroforestry from the point of view of this participant. Such inaccuracy and the ability to interpret the image was even more interesting when participants tried fitting the images to their own landscape visions, as we show in the discussion below about the agroforestry image. The imperfection, despite raising concerns and shifting discussions, still allowed for more conversations and sparked imagination as noted by previous research (Guridi, Hwang, et al., 2025; Valença et al., 2025).

P7: "Okay. So are these trees here or it almost looks like vines?"
Facilitator: "You can think about them maybe as small trees still growing, or you can think about it as something else. What do you think about them?"
P8: "I mean, that could be an orchard."
P7 "That's what I'm looking at. It could almost be an orchard. Maybe it's an apple orchard."
P8: "Well, yeah. I mean, you really don't know what species there are. So you may have fruit nut production. I mean, in Indiana, I mean, you could easily make this an orchard and have some cherry trees, some apple trees. I mean, there's a lot of diversification you can have in this scenario. It doesn't have to be all hardwoods."
P7: "I like the orchard idea."
Facilitator: "You like it? Would you like to write it down? Thank you."
P2: "I would say an orchard, at least on the right."
P8: "And yeah, maybe even up in here as well."
P2: "Yeah, there could be something starting."
P8: "It could be. Again, this is an AI-generated photo."
P7: "Right. But still, it's pretty fun."
P8: "You got to give it some liberties."

In terms of concerns raised by inaccuracies, the absence of people was a critical issue. A participant noted: *"But I'm worried that this is the AI's version of what they think the landscape should be. There are no people in the landscape."* The absence of people and built-up areas from the images created a feeling that these images are devoid of life, which is problematic, even for sessions focused on proposal modification: *"Again, these are all devoid of life… It's really not set up, I guess, for people to be out there. There's no power line. Nothing. No water tower. No nothing."* In addition to these concerns, inaccuracies also led to conversations focusing on minor details rather than the broader landscape, shifting attention away from key discussions as participants get busy criticizing the images. This includes criticism of plant species or livestock: *"The trees are kind of fuzzy so I can't really say anything about a particular tree;"* criticism to the accuracy of scale: *"I wonder what the scale here is. In a way, when you look at the horizon, it's dissimilar;"* and criticism of the inaccuracy of the horizon line representation: *"So where are the mountains in the background of the Midwest?"*

5.2. The new agroforestry image based on stakeholder responses in Illinois and Iowa

Participatory feedback on "keep" and "change" categories from Illinois and Iowa meetings informed the updated version of the agroforestry image. The figure below (Fig. 7) shows the agroforestry images before and after community engagement sessions. It is clear that the updated image addresses some of the major themes identified from the two meetings data (please see section 4.4 above and Appendix G for a detailed analysis of the results). For example, the new image kept the existing crop diversity, added more crop diversity, and included a diversity of livestock in the system. The new image also addressed the ecosystem and the natural resources by including more green areas, and two bodies of water. In terms of community aspects, the new image showcases a town in the background, and people engaged in the agroforestry landscape. The agricultural system and the community were also supported by roads, a cellphone broadcasting tower, and water tanks that showcase the presence of infrastructure.

5.3. The new agroforestry image based on stakeholder responses in Indiana

Keywords from the stickers posted on the agroforestry image in

Fig. 7. Left: Result of (Step 2) of the agroforestry image. Right: the updated agroforestry image (Result pf Step 5) after the Illinois and Iowa participatory sessions. Initial prompt of the image on the right:"Aerial wide angle watercolor rendering of the Midwest. The image shows rolling hills and flat plains. Largescale agroforestry cultivation. Groves of organized tree lines o of chestnut, hazelnut, and diverse fruit trees with small crops under the trees. Some farms have mature trees and some have small trees. Different crops are cultivated under the tree canopy (understory crops), including vegetable crops, cash crops, shrubs, herbs. A narrow water stream is visible. A main street leads to a town in the background, adjacent to it are solar panels. In the middle ground there is livestock. There is also a storage building and a farmhouse. A riparian buffer locates on the edge of this farm. Adjacent to the town are processing facilities for fruit and nuts production." The image was edited, both in Midjourney and Photoshop.

Indiana prompted the updated image of the agroforestry, but the process was not straightforward. The first few results that Midjourney yielded were not accurate representations of the prompt, which was crafted from community responses. Nevertheless, after more experimentation for an hour, and after discarding around 300 images, we generated an image that is not perfect but addresses some of the community feedback written on the stickers, such as keep "orchard;" keep "cover between trees;" add "cattle;" add "roads;" add "homes;" among other keywords. The figure below (Fig. 8) shows the first Midjourney output compared to the one we developed within an hour.

6. Discussion

As we detail below, our final method is an effective and efficient means for streamlining text-to-image conversion in participatory processes. Balancing effectiveness and efficiency required developing 'controlled imperfects;' that is, having "good enough" images that reasonably approached reality such that they aided rather than hindered discussions. Finally, we close with a number of suggestions others can use in their processes to adapt and improve this method.

6.1. Simplifying the big text-to-image process

Typically, the process of regenerating images from text requires a "text compression" process to distill the essential information from long texts into selected keywords (Konarieva et al., 2019). This process is often time-consuming, requires specialized training in qualitative methods, and can involve subjective decisions in keyword selection by the researchers (Alkhateeb et al., 2024; Guridi, Hwang et al., 2025). In contrast, our approach uses stickers to collect already "compressed" data in the form of a few keywords selected by the participants. The stickers exclude redundant information that is unnecessary for image generation. While we also audio-record discussions to capture the full context, our sticker method does not require the in-depth analysis and interpretation typically required for qualitative research, as our intent was not to develop theory or richly describe a case. Transcripts and stickers were used solely to inform image revision and the context within which revisions were suggested. Our method streamlining enabled more efficient image development and reduced complexity, an important contribution to the literature (please see (Fig. 9) below). This approach is ideal in cases with high engagement across multiple community

Fig. 8. Left: the four options that Midjourney provided for the prompt "Aerial bird view perspective watercolor rendering of a midwestern grid landscape that has a diversity of orchards with different trees in each orchard, with livestock grazing under the trees, with people walking around and tourism, a town in the background, with wind turbines and solar power, with farm buildings, with crops and cover crops, with wetland, with pond and habitat, with tractor." Right: the updated agroforestry image after the community session in Indiana.

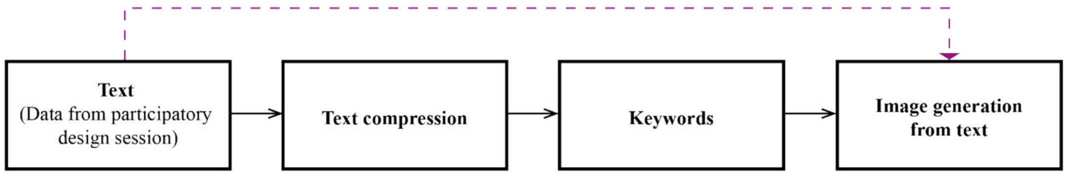

Fig. 9. Big text data, such as transcripts, often need to be analyzed to select few keywords needed for prompt engineering to inform image generation. Our approach streamlines the process by directly collecting the keywords from community engagement sessions. The figure is adapted from (Konarieva et al., 2019).

sessions that normally require significant analytical demands (Guridi, Cheyre, et al., 2025) as our approach help minimizing such analysis. In addition, this streamlined approach is crucial for a controlled "real-time" text-to-image participatory approach (see Future Directions section).

6.2. Finding the optimal pace: Neither instant nor overly slow

Text-to-image models hold promise for community engagement in design due to their rapid image generation capabilities, an advantage for facilitating instant modifications and continuing community conversations (Bova, 2025; Guridi, Hwang, et al., 2025). However, such real-time integration poses concerns, many of which relate to the images' content (Du et al., 2023). Therefore, the results of generative image models must be questioned and critically evaluated (Guridi, Cheyre, et al., 2025; Oppenlaender, 2022; Valença et al., 2025) to avoid presenting "unexpected" visual outputs to the community stakeholders that might pose critical concerns (Guridi, Hwang, et al., 2025). While some researchers still chose to generate instant images as part of the community engagement activity (e.g., Bova, 2025; Guridi, Hwang, et al., 2025), others chose to create the generative images over an extended period of time (after the participatory process) before sharing the results back to the community (e.g., Alkhateeb, 2024). The first approach poses risks of using "unexpected" visuals as we mentioned, and the second might help avoid that risk. Yet, with its slow pace; it uses generative tools in a time-consuming manner that does not harness the full potential of generative text-to-image models.

Through our approach, we first tested whether we could create high-quality images that address most of the community inputs. The process was time-consuming, involving extensive data analysis and hours of experimentation with Midjourney to create a perfect image that "slowly emerges over time" (Oppenlaender, 2022). Although we achieved high-quality results, the process was lengthy and did not meet our objective of using generative tools efficiently. Our initial approach was actually focused on customizing the output image, but the literature pointed out that the process itself is more important (Guridi, Hwang, et al., 2025; Valença et al., 2025). In our new approach of data analysis and image generation (presented using Indiana meeting data in Step 4 (option b) and Step 5 (option b), and further advance in the Future Directions section below), we suggest a balance between instant generation and slow pace, making sure that researchers have the chance to calibrate the image outputs before presenting them back to the community, while also not using the generative text-to-image tools in a slow pace that mimics the use of traditional visualization tools, such as Photoshop.

6.3. 'Controlled imperfect' generative images

Recently published research suggested that imperfect images can be more effective for community discussions as they allow for more conversation than perfectly crafted images (Guridi, Hwang, et al., 2025), meaning that fine-tuning the images is unnecessary, and even not recommended. Our initial approach's inability to balance quality and efficiency, and the recent research suggestion not to focus on producing realistic images led us to revise our method. We realized that detailed data analysis was not necessary prior to image generation. Instead, we could use community keywords to craft our prompts. As we crafted the prompts and quickly tried them in Midjourney, the results did not match our expectations based on community discussions and sticker notes. At the same time, these results fit the description of "conversational imperfects" suggested by (Guridi, Hwang, et al., 2025), which, although beneficial in some community engagement processes, were too far from our goals and would likely be problematic in future engagement sessions. After experimenting with Midjourney for an hour, we achieved an image output that balanced quality and time, yielding what we call 'controlled imperfects.' These images, while imperfect, are reasonable enough for community discussions while avoiding potential issues with inaccurate representations. This approach enables us to leverage the speed of generative text-to-image technologies while maintaining control in a way that enables fruitful conversation, not hindering it. Fig. 10 below illustrates the difference between "fake perfects", "conversational imperfects," and our 'controlled imperfects' of the agroforestry landscape. We believe that designers can take our updated approach further to enable other forms of integrating generative text-to-image tools in participatory design (see Future Directions below).

7. Future directions

This research aimed to explore new ways of integrating generative text-to-image tools in participatory settings, benefiting from their real-time potential (e.g., Guridi, Cheyre, et al., 2025), while maintaining control over the results. Our approach of collecting readily available data for prompt crafting, and generating 'controlled imperfect' images seems promising. We believe these contributions can advance participatory design by enabling quick and controlled use of generative tools. The figure below (Fig. 11) presents a method we think is possible to adopt by researchers and designers as they engage with the community. Building on our DCB case study, this method starts by finding the suitable generative text-to-image model for the specific design need (e.g., visualizing a building renovation proposal might need a different generative model than street design). Then, the practitioners can create a design proposal before meeting the community. Following that, the community engagement session, in a World Café format or any other format, can be used to collect keywords to feed the next round of text-to-image generation. These keywords can be grouped and prioritized by the community members within a few minutes. Following that, practitioners can step away from community members, quickly develop 'controlled imperfect' images within a short time, and then come back to the stakeholders with a new scenario to start the process again within the same workshop setting (participants may be engaged in a different, probably supportive, activity meanwhile). This approach may enable the development of mature design visuals through an iterative process involving multiple rounds of data collection, grouping, and image generation. By these means, our suggested approach can "ground the verbal responses and allow deeper conversations" as participants work on co-editing the regenerative images (Guridi, Cheyre, et al., 2025). Adopting this approach might be particularly valuable for designers who aim to facilitate collaborative design workshops within a condensed time-frame, such as a one-day format, with the goal of developing detailed designs with community stakeholders. Although we have not tested this approach yet, we think it holds promise and we hope other researchers can take this approach further. Given the speed at which AI is being incorporated into planning and applied research and design, we expect

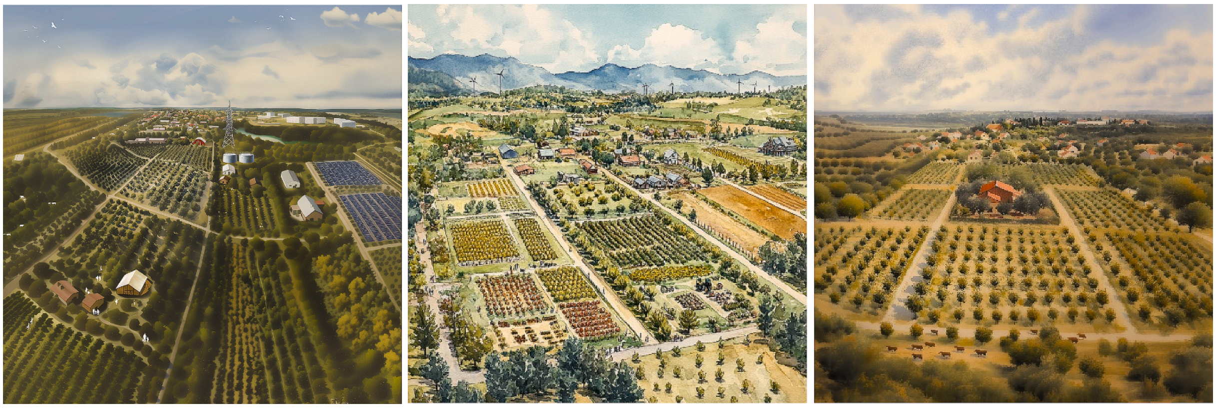

Fig. 10. Left: "Fake perfect" agroforestry representation based on the Illinois and Iowa meetings. Middle: a "conversational imperfect" image of the agroforestry system based on Indiana meeting. Right: a controlled imperfect representation of agroforestry based on Indiana meeting.

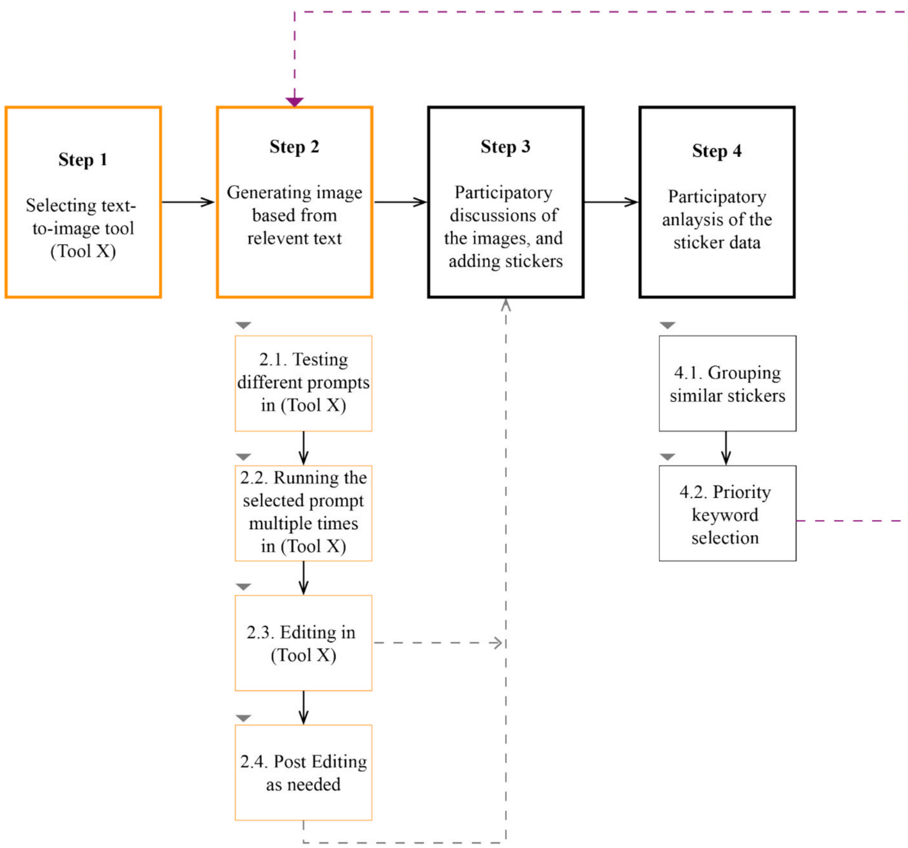

Fig. 11. An iterative method for integrating generative text-to-image tools in community design workshops. The process involves multiple cycles of community engagement, keyword collection, and rapid generation of 'controlled imperfect' images, allowing for collaborative design development within a condensed timeframe. The orange boxes indicate steps that researchers may complete independently without community presence in order to maintain control over the visual outcome. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

many exciting developments in the next few years that we can also incorporate into our work.

8. Limitations

Rather than focusing on limitations and considerations of generative tools, which are discussed in other literature (e.g., Albaghajati, Bettaieb, & Malek, 2023; Betker et al., 2023; Du et al., 2023), we chose to present the limitations of our research. One limitation comes from our request to participants not to duplicate what other participants already posted on the images, which, while promoting breadth, limited our ability to accurately identify prominent themes when grouping similar responses, as we could not quantify the frequency of duplicated ideas. A revised approach to be tested would examine whether it's more effective to have people include their salient thoughts rather than generate new ideas if theirs was already discussed and written by others. Also, our tested approach can create a power imbalance, with researchers prioritizing keywords based on their count. In contrast, our suggested Future Direction approach shifts power to participants, allowing them to determine emphasis. However, it may still be influenced by the presence of the researcher or other individuals in the room. Another limitation is that while sticker data may be convenient for image generation, we still see a need to go over the transcripts to ensure accuracy and context understanding. Another key limitation of our study lies in not testing the data analysis phase and image generation (Steps 4 and Step 5, option b) within the participatory process, nor did we test the suggested approach proposed in the Future Directions section. In addition, our suggested Future Direction approach requires training the facilitators of the community sessions (or another person in the research team) on prompt engineering, generating images, criticizing the results, and editing them in a rapid time (e.g., Guridi, Hwang, et al., 2025). This means spending significant time learning these skills prior to the community session, especially if the session includes working with participants on multiple proposals, meaning that multiple facilitators need to be experts in the use of the selected generative model. Also, we expect that the image developer (and the team) will be under pressure while working on a 'controlled imperfect' in a short time frame, especially with the current limitations of generative tools in prompt following (Betker et al., 2023; Liu & Chilton, 2023; Wasielewski, 2023), meaning that the final 'controlled imperfect' image might still be behind the expectations.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Midjourney, DALL.E, and Adobe Firefly in order to generate the images of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

CRediT authorship contribution statement

Ishraq Awashra: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Aaron W. Thompson:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Kristin Floress:** Conceptualization, Writing – review & editing. **J.Gordon Arbuckle:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation. **Sarah P. Church:** Writing – review & editing, Validation, Supervision, Methodology, Funding acquisition, Conceptualization. **Ken Genskow:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation. **Linda S. Prokopy:** Writing – review & editing, Validation, Supervision, Resources, Methodology, Investigation, Funding acquisition, Conceptualization. **Yichao Rui:** Supervision. **Omar Tesdell:** Supervision.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2025.105464.

Data availability

Data related to AI generated images, and data collected during the participatory sessions will be made available on request. Data of individual participants is confidential.

References

Albaghajati, Z. M., Bettaieb, D. M., & Malek, R. B. (2023). Exploring text-to-image application in architectural design: Insights and implications. *Architecture, Structures and Construction, 3*(4), Article 4. https://doi.org/10.1007/s44150-023-00103-x

Alkhateeb, G., Storie, J., & Külvik, M. (2024). Post-conflict urban landscape storytelling: Two approaches to contemporary virtual visualisation of oral narratives. *Land, 13*(4), Article 4. https://doi.org/10.3390/land13040406

Al-Kodmany, K. (2010). Visualization tools and methods for participatory planning and design. *Journal of Urban Technology, 8*(2), Article 2. https://doi.org/10.1080/106307301316904772

Al-Kodmany, K. (2020). Public participation and methods of visual communication. In *Tall Buildings and the City: Improving the Understanding of Placemaking, Imageability, and Tourism* (pp. 83–119). Springer. doi: 10.1007/978-981-15-6029-3_4.

Asprooth, L., Arbuckle, J. G., Traldi, R., Church, S. P., Floress, K., Gramig, B. M., Margenot, A. J., Maynard, E. T., Thompson, A. W., & Torres, A. P. (2025). To diversify or not to diversify: A preliminary report on farmers' perspectives on diversification in the US Midwest. *Renewable Agriculture and Food Systems, 40*, e14.

Betker, J., Goh, G., Jing, L., Brooks, T., Wang, J., Li, L., Ouyang, L., Zhuang, J., Lee, J., Guo, Y., Manassra, W., Dhariwal, P., Chu, C., Jiao, Y., & Ramesh, A. (2023). *Improving Image Generation with Better Captions*.

Bova, P. (2025). Artificial intelligence and co-visioning: The use of images generated with AI Tools in Participatory Planning. In P. Gallo, S. E. Bibri, F. Alberti, A. R. Matamanda, C. Piselli, H. Rabiei, R. Romano, & A. Ozcan- Buckley (Eds.), *Urban and Transit Planning* (pp. 295–304). Springer Nature Switzerland. doi: 10.1007/978-3-031-75709-9_25.

Creswell, J. W. (2009). *Research Design-Qualitative, Quantitative, and Mixed Methods Approaches*. California: SAGE.

Du, J., Ye, X., Jankowski, P., Sanchez, T. W., & Mai, G. (2024). Artificial intelligence enabled participatory planning: A review. *International Journal of Urban Sciences, 28* (2), 183–210. https://doi.org/10.1080/12265934.2023.2262427

Fernberg, P. (2024). *Artificial intelligence in landscape architecture: A survey of theory, culture, and practice* [Utah State University]. https://digitalcommons.usu.edu/etd2023/152.

Fernberg, P., & Chamberlain, B. (2023). Artificial intelligence in landscape architecture: A literature review. *Landscape Journal, 42*(1), Article 1. https://doi.org/10.3368/lj.42.1.13

Fernberg, P., George, B. H., & Chamberlain, B. (2023). *Producing 2D Asset Libraries with AI-powered Image Generators*. *8*. doi: 10.14627/537740020.

Filor, S. W. (1994). The nature of landscape design and design process. *Landscape and Urban Planning, 30*(3), 121–129. https://doi.org/10.1016/0169-2046(94)90051-5

Fredericks, J., Hespanhol, L., Parker, C., Zhou, D., & Tomitsch, M. (2018). Blending pop-up urbanism and participatory technologies: Challenges and opportunities for inclusive city making. *City, Culture and Society, 12*, 44–53. https://doi.org/10.1016/j.ccs.2017.06.005

Gazvoda, D. (2002). Characteristics of modern landscape architecture and its education. *Landscape and Urban Planning, 60*(2), 117–133. https://doi.org/10.1016/S0169-2046(02)00064-6

Guridi, J. A., Cheyre, C., Goula, M., Santo, D., Humphreys, L., Souras, A., & Shankar, A. (2025). Image generative ai to design public spaces: A reflection of how AI could improve co-design of public parks. *Digit. Gov.: Res. Pract.*, *6*(1), 7:1–7:14. doi: 10.1145/3656588.

Guridi, J. A., Hwang, A. H.-C., Santo, D., Goula, M., Cheyre, C., Humphreys, L., & Rangel, M. (2025). From fake perfects to conversational imperfects: Exploring image-generative ai as a boundary object for participatory design of public spaces. *Proceedings of the ACM on Human Computer Interaction*, *9*(2), CSCW014:1-CSCW014:33. doi: 10.1145/3710912.

Hakimshafaei, M. (2023). *Survey of Generative AI in Architecture and Design* (M.S., University of California, Santa Cruz). University of California, Santa Cruz, United States – California. Retrieved from https://www.proquest.com/docview/2812330639/abstract/498B5EC8263C4027PQ/1.

Hester, R. T. (2012). Scoring collective creativity and legitimizing participatory design. *Landscape Journal, 31*(1/2), 135–143.

Huang, R., Lin, H., Chen, C., Zhang, K., & Zeng, W. (2024). *Plantography: Incorporating iterative design process into generative artificial intelligence for landscape rendering*. 1–19.

Jackson, D. L., & Jackson, L. (2002). *The farm as natural habitat: Reconnecting food systems with ecosystems*. Island Press.

Jackson, L. L. (2008). Who "Designs" the agricultural landscape? *Landscape Journal*, *27* (1), Article 1. https://doi.org/10.3368/lj.27.1.23.

Kajosaari, A., Schorn, M., Hasanzadeh, K., Rinne, T., Rossi, S., & Kyttä, M. (2024). Beyond the backyard: Unraveling the geographies of citizens' engagement in digital participatory planning. *Environment and Planning B: Urban Analytics and City Science, 52*(4), 770–788. https://doi.org/10.1177/23998083241271460

Konarieva, I., Pydorenko, D., & Turuta, O. (2019). *A survey of methods of text-to-image translation*.

Lee, H. (2025). Designing and evaluating landscape proposals with generative AI ChatGPT - urban plaza design via landscape firm style emulation with educational potential. *Journal of the Korean Institute of Landscape Architecture, 53*(2), 116–132. https://doi.org/10.9715/KILA.2025.53.2.116

Li, C., Zhang, Z., Wu, H., Sun, W., Min, X., Liu, X., Zhai, G., & Lin, W. (2023). *AGIQA-3K: An open database for AI-generated image quality assessment* (arXiv:2306.04717). arXiv. doi: 10.48550/arXiv.2306.04717.

Li, M., & Amoroso, N. (2023). An early look at applications for artificial intelligence visualization software in landscape architecture. *Journal of Digital Landscape Architecture, 8*. https://doi.org/10.14627/537740057

Li, P., Li, B., & Li, Z. (2024). Sketch-to-architecture: Generative ai-aided architectural design. *arXiv Preprint arXiv:2403.20186*.

Liu, V., & Chilton, L. B. (2023). *Design guidelines for prompt engineering text-to-image generative models* (arXiv:2109.06977; Issue arXiv:2109.06977). arXiv. doi: 10.48550/arXiv.2109.06977.

Lovett, A., Appleton, K., Warren-Kretzschmar, B., & Von Haaren, C. (2015). Using 3D visualization methods in landscape planning: An evaluation of options and practical issues. *Landscape and Urban Planning, 142*, 85–94. https://doi.org/10.1016/j.landurbplan.2015.02.021

Oppenlaender, J. (2022). The creativity of text-to-image generation. In *Proceedings of the 25th international academic Mindtrek conference* (pp. 192–202). https://doi.org/10.1145/3569219.3569352

Phillips, C., Jiao, J., & Clubb, E. (2024). Testing the capability of AI Art tools for urban design. *IEEE Computer Graphics and Applications, 1–8*. https://doi.org/10.1109/MCG.2024.3356169

Ploennigs, J., & Berger, M. (2023). AI art in architecture. *AI in Civil Engineering, 2*(1), 8. https://doi.org/10.1007/s43503-023-00018-y

Prokopy, L. S., Carlson, S., English, L., Church, S., Atallah, S., Heaton, E., Margenot, A., Floress, K., Graming, B., Arbuckle, J., Gassman, P., Genskow, K., Kelleher, P., Armstrong, S., Hallett, S., Kaplan, I., LaRose, S., Maynard, E., Thompson, A., … Tiboris, M. (2020). *#DiverseCornBelt: Enhancing rural resilience through landscape diversity in the Midwest: Project Summary*. Unpublished.

Prokopy, L. S., Gramig, B. M., Bower, A., Church, S. P., Ellison, B., Gassman, P. W., Genskow, K., Gucker, D., Hallett, S. G., Hill, J., Hunt, N., Johnson, K. A., Kaplan, I., Kelleher, J. P., Kok, H., Komp, M., Lammers, P., LaRose, S., Liebman, M., & Ulrich-Schad, J. D. (2020). The urgency of transforming the Midwestern U.S. landscape into more than corn and soybean. *Agriculture and Human Values, 37*(3), Article 3. https://doi.org/10.1007/s10460-020-10077-x

Purdue, CCED. (2024). *AI Application for Rural Landscape Design | Purdue*. University Center for Community & Environmental Design. Purdue Center for Community and Environmental Design. https://www.purdue.edu/hla/sites/thompsonlab/otherpublications/ai-application-for-landscape-architecture/.

Sanoff, H. (2000). *Community participation methods in design and planning*. Wiley.

Sanoff, H. (2016). *Visual research methods in design (routledge revivals)*. Routledge. doi: 10.4324/9781315541822.

Schlickman, E., Li, X., & Wang, D. (2024). Spot the bots: analyzing text-to-image outputs for the field of landscape architecture. *Journal of Digital Landscape Architecture, 9*. https://doi.org/10.14627/537752071

Schlickman, E., & Magana-Leon, A. (2024). Employing generative technology in urban design: an aid or a threat? *Journal of Digital Landscape Architecture, 9*. https://doi.org/10.14627/537752072

Seddon, G. (1986). Landscape planning: A conceptual perspective. *Landscape and Urban Planning, 13*, 335–347. https://doi.org/10.1016/0169-2046(86)90051-4

Senbel, M., & Church, S. (2011). Design empowerment: The limits of accessible visualization media in neighborhood densification. *Journal of Planning Education and Research, 31*, 423–437. https://doi.org/10.1177/0739456X11417830

Senem, M. O., Tuncay, H. E., Koç, M., & As, I. (2024). Generating landscape layouts with GANs and diffusion models. *Journal of Digital Landscape Architecture*, 137–144.

The World Café Community Foundation. (2015a, July 4). A Quick Reference Guide for Hosting World Café. Retrieved May 27, 2024, from The World Cafe website: https://theworldcafe.com/tools-store/hosting-tool-kit/.

The World Café Community Foundation. (2015b, July 4). World Cafe Method. Retrieved February 24, 2024, from The World Cafe website: https://theworldcafe.com/key-concepts-resources/world-cafe-method/.

Traldi, R., Asprooth, L., M. Usher, E., Floress, K., Arbuckle, J. G., Baskerville, M., Church, S. P., Genskow, K., Harden, S., Maynard, E. T., Thompson, A. W., Torres, A. P., & Prokopy, L. S. (2024). "Safer to plant corn and beans"? Navigating the challenges and opportunities of agricultural diversification in the U.S. Corn Belt. *Agriculture and Human Values*, *41*(4), 1687–1706. doi: 10.1007/s10460-024-10570-7.

Valença, G., Azevedo, C., Moura, F., & Morais de Sá, A. (2025). Creating visualizations using generative AI to guide decision-making in street designs: A viewpoint. *Journal of Urban Mobility, 7*, Article 100104. https://doi.org/10.1016/j.urbmob.2025.100104

Wang, J., Duan, H., Liu, J., Chen, S., Min, X., & Zhai, G. (2023). *AIGCIQA2023: A large-scale image quality assessment database for AI generated images: from the perspectives of quality, authenticity and correspondence* (arXiv:2307.00211). arXiv. doi: 10.48550/arXiv.2307.00211.

Wasielewski, A. (2023). *"Midjourney can't count": Questions of representation and meaning for text-to-image generators*.

Xing, Y., Gan, W., & Chen, Q. (2025). Artificial intelligence in landscape architecture: A survey. *International Journal of Machine Learning and Cybernetics*. https://doi.org/10.1007/s13042-025-02536-w