Image Generative AI to Design Public Spaces: a Reflection of How AI Could Improve Co-Design of Public Parks

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Image generative AI (IGAI) could change how policymakers engage with the public to design public spaces, facilitating how designers translate the public's desires into features. However, using IGAI has challenges, such as encoded biases, which might reinforce stereotypes and harm underrepresented communities. We conducted a case study to explore how using IGAI alters the co-design process of public parks through public engagement. We use data collected from interviews with immigrants discussing the Puente Hills Landfill Park design in Los Angeles, which will re-purpose a former landfill into a new public park. We use Dream Studio as a Design Probe, generating images from the interviewees' insights and critically reflecting on the design process through internal interviews and a reflective workshop. We analyze our case in three domains: Opportunities, Risks and Challenges, and Features and Requirements. In the opportunities domain, we discuss how the enhanced translation of words to images changes the relationship between stakeholder engagement, multiplicity, and efficiency. In the risks and challenges domain, we discuss how IGAI might enhance power imbalances and biases. Finally, we reflect on what features would ease the safe and responsible use of IGAI to engage citizens in co-designing public parks.

CCS Concepts: • **Human-centered computing** → **Human computer interaction (HCI);** • **Social and professional topics** → *Computing/technology policy* • **Applied computing** → *Arts and humanities;* • **Computing methodologies** → **Artificial intelligence**;

Additional Key Words and Phrases: Image-generative AI, landscape architecture, design, public spaces

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1 INTRODUCTION

Designing inclusive public spaces is a complex process that requires integrating conflicting views often unknown to the planner and the designer. Currently, the best practice to understand stakeholders' preferences is to use participatory processes combined with an iterative design process. Integrating **Image-Generative Artificial Intelligence (IGAI)** Systems in these processes can improve how public spaces are co-designed. By efficiently enabling the translation of the public's requirements into images, and in this way, more rapidly iterating design ideas with stakeholders, designers, and public officials can better tailor public spaces to the needs of the communities for which they are intended. However, using IGAI entails many challenges ranging from usability to potential risks, such as reaching conclusions based on results arising from biased datasets that could lead to further marginalizing minority and vulnerable groups [e.g., 3, 6]. Thus, a more comprehensive understanding of how landscape architects could use IGAI is needed to foster its adoption, harnessing the imagined benefits while preventing potential harm.

We completed a case study using Dream Studio to propose images from inputs gathered from immigrants for the transformation of the Puente Hill Landfill in Los Angeles into a public park. Our study focuses on the process of landscape architects using the IGAI to sketch images and their reflection on the opportunities, risks, and challenges that arise from this exercise. The study is part of a broader project analyzing how participatory and co-design methods can improve how public spaces are also designed for integrating migrants into their new communities.

Our analysis focuses on three domains: Opportunities, Risks and Challenges, and Features and Requirements. In the opportunities domain, we discuss how the enhanced translation of words to images changes the relationship between stakeholder engagement, multiplicity, and efficiency. In the risks and challenges domain, we discuss how IGAI might enhance power imbalances and biases. Finally, we reflect on what features would ease the safe and responsible use of IGAI and the potential changes to the design processes and landscape architects' professional profiles. Our case study contributes to identifying areas of interest for future inquiry in Human-Computer Interaction, Landscape Architecture, and Public Participation.

2 BACKGROUND

Designing public spaces is a wicked problem involving complex multi-layered processes of decision-making and iterative reformulation of sets of challenges with conflicting stakeholders in which the issues, responses, methods, and goals might be unknown and contested [32]. To define what to design and the level of performance (i.e., design objectives and feasibility constraints) [21] and incorporate how different cultures and identities desire to be represented in the built environment [19], public officials and landscape architects have developed an extensive repertoire of methods for participatory processes and iterative design exploration [20, 32–34, 39]. However, most stakeholders are not design experts, so they might be unable to vocalize specific requirements or ideas unless presented with support material, usually in visual forms [21, 34]. Thus, to successfully engage with the public, practitioners typically rely on information technologies (ICTs) to assist with a variety of outreach, mediation, and analysis tasks [8, 36]. However, several challenges remain to completely integrate ICTs in fully understanding and integrating the spatial implications and particular difficulties of underrepresented communities such as immigrants [12, 13, 19, 23].

Generative design uses computer-based generative methods to improve the efficiency and results of traditional design methods [21]. Generative Urban Design models are yet to address the complexity of the required elements, focusing primarily on single-element design [21], especially streets and buildings [25, 52]. Thus, most studies in these domains focus on generating solutions satisfying quantitative performance objectives such as economic profitability or optimal energy consumption [22, 49] while failing to address qualitative elements such as local characters, design aesthetics, atmospheres, and contextual integration [21].

Generative AI (**GenAI**) refers to AI systems that generate novel content (e.g., text, images, videos) from large training datasets. Diffusion Probabilistic Models [18, 45] and, in particular, Stable Diffusion models [14, 38] can generate complex images through text entries which can also be complemented with other inputs (e.g., images) (see Zhang et al., [53] for a review on current IGAI methods). Since the Stable Diffusion models, IGAI has grown in the last two years with several applications to edit and create artistic and realistic images (see Gozalo-Brizuela and Garrido Merchan [17] for a review of GenAI applications).

Using AI systems in the public sector entails many challenges [24, 48]. Societal issues such as automation of labor, acceptance/trust in AI systems, and human-to-machine communication [48, 51] are at the core of the interaction of practitioners with stakeholders and the public to co-design public spaces. For instance, practitioners hold power when planning the interactions and using AI, which impacts how the relationships will be defined [4, 7, 10]. However, practitioners usually do not fully understand AI systems nor their risks, and there is a lack of specific guidelines to make AI systems' providers accountable [11, 31, 44]. Additionally, further understanding is needed to address organizational challenges to implement trustworthy AI to enhance the co-design of public spaces, including financial, infrastructure, expertise, and adoption mechanisms [16, 35, 48, 51]. For an exhaustive review of variables influencing AI adoptions in public administration, see Madan and Ashok [26].

In particular, using GenAI systems entails new risks that might never be fully uncovered due to their dynamism and context dependence. Models trained on large-scale unfiltered data can contribute to the harm of people [53]. For instance, IGAI can generate offensive or insulting content [40] or be biased in cultural [46], racial [5], or other ways; IGAI can create false electronic evidence [41], which can be hard to detect [9, 37]; and increase plagiarism and profit shifting in the art industry [15]. Weidinger et al., [50] propose a taxonomy of risks for **large-scale Language Models** (**LLMs**), many of which can also be adapted to IGAI: (1) Discrimination, Hate speech, and Exclusion; (2) Information Hazards; (3) Misinformation Harms, (4) Malicious Uses; (5) Human-Computer Interaction Harms; and (6) Environmental and Socioeconomic Harms. That said, distilling best practices to identify pitfalls and prevent harm is an emerging field of study to which we aim to contribute.

Our case illustrates the exploratory phase of a research project that aims to contribute to understanding the role of IGAI in participatory processes for designing public spaces. In particular, we explore how the advancements in IGAI could change how landscape architects engage with stakeholders and the public to co-design public spaces.

3 METHODS

This case study is part of a broader project studying how to map immigrant preferences and uses of public space through technology to foster inclusive design and management of the urban commons. To do so, we have developed and tested different methodologies to engage with the public and gather information that decision-makers and landscape architects could use to design a public park. The setting of our study is the Puente Hills Landfill Park near Los Angeles, California. This project is transforming the former second-largest landfill in the U.S. into a public park. To conduct our study, we partnered with Studio MLA, the firm in charge of the project's current design phase. Our partnership has allowed us to collaborate with local stakeholders in the participatory processes organized by the firm and incorporate new elements into the processes. We have conducted semi-structured interviews, co-design workshops, and online surveys through social media advertising to gather different inputs from immigrants in the Puente Hills Area. A significant challenge that has become evident in this process and

that the use of IGAI could alleviate is translating the insights we have gathered into spatial parameters and design ideas while collaborating with the public.

3.1 Puente Hill Landfill

The Puente Hills Landfill opened in 1957 in the San Gabriel Valley, California, and operated for 56 years until October 31, 2013. During its operation, it was one of the largest landfills in the US, with more than 490 feet in height and covering an area larger than a square mile. More than 150 million tons of trash are buried in it [29]. The park is located in a predominantly immigrant population (e.g., 70% Latinx/Hispanic and 19% Asian) in a zone with less than 1 acre of parks per 1,000 residents [29].

Los Angeles County Department of Parks and Recreation started a project to re-purpose the landfill into a public park. Since the Kickoff of the project's current stage in 2022, more than 1,300 participants have contributed through different means (e.g., text messages, workshops, interviews, interactive hikes). Studio MLA is currently in the Schematic Design stage, and the anticipated completion date for the phase is 2026. For this particular study, the research team collected the data used to prompt the system through interviews in which Studio MLA facilitated the recruitment of the participants.

3.2 Dream Studio as a Design Probe

We used Dream Studio as a design probe [28] to learn how landscape architects could use IGAI to explore design ideas and interact with the public when doing so. Dream Studio is a service based on the open-source Stable Diffusion model [38] developed by Stability AI, which enables people to use an IGAI without any software installation, coding knowledge or local GPU [1, 2]. Users own the images they create through Dream Studio and use a pay-per-image model with a cost of $10 per 1,000 generation credits, which serve for approximately 5,000 images.

Dream Studio offers several options to tailor the images. The core prompt is a free/text box, constituting the center of the image around which the rest is built, but with no other tailoring, images will be generic. The second setting is a drop-down menu for Style, which can make the image closer to the users' needs. Users can specify an artistic style and add additional elements to improve the prompt. However, the further they personalize the image, the harder it is to get a consistent image with all the details in the prompt. A second feature is Prompt Weighting, allowing users to define a hierarchy and the number of elements to incorporate (e.g., colors, objects) in a composition, increasing control over the synthesis. A third feature is negative prompting, allowing users to instruct the model on what not to generate. Finally, users can upload images to generate variations from a starting point and customize settings such as image size, count, generation steps, prompt strength (i.e., how much the image will portray the prompt), and seed (i.e., initial noise). We chose Dream Studio for our case study because it provides further flexibility and customization compared to DALL-E2 and Midjourney, which was valuable for the design team. However, further studies should compare our results to DALL-E2 and Midjourney, which stand out in other features such as image quality and post-editing capabilities.

Between June and November, we assembled a team of professors and students in Landscape Architecture who participated in the Puente Hills Landscape Project (see Table 1) to work and document the experience of working with Dream Studio. In this exploration phase, they did not engage directly with the public but used the data collected through interviews and surveys during the first phases of the broader project. The process was organized in two stages. During the first stage, the team focused on learning how to use Dream Studio and testing it using reference images of parks mentioned in the interviews with immigrants. The second stage consisted of testing Dream Studio without reference images by refining the prompts and using the software's more advanced features.

3.3 Debriefing the Exploration Phase

We conducted semi-structured interviews with four team members more deeply involved in using Dream Studio (i.e., Maria, Duarte, Xiaochang, and Achilleas) to distill the main insights from the architects' experience

Table 1. Testing Team

Team Member	Education
Maria Goula	Ph.D. in Landscape Design Theory & Master in Landscape Architecture
Duarte Santo	Master in Architecture & Master in Landscape Architecture
Xiaochang Qiu	Master in Landscape Architecture Student
Yike Xu	Master in Landscape Architecture Student
Alberto Salgado	Master in Landscape Architecture Student
Aishwarya Shankar	Master in Landscape Architecture Student
Jichu Zhang	Undergraduate Student with Major in Landscape Architecture
Achilleas Souras	Undergraduate Student with Major in Architecture

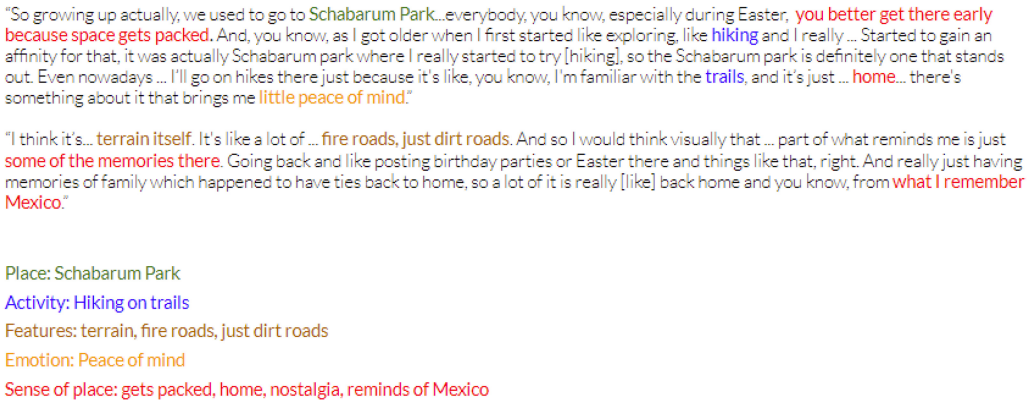


Fig. 1. Quote translation into aspects of the convivial public space framework.

experimenting with Dream Studio. The interview was prepared and conducted by one of the non-landscape architecture authors (i.e., Jose Guridi).

Based on the interviews and the process notes, we organized a 2-hour reflection workshop to hone the insights, discussing the main opportunities, risks and challenges, the system's features, and how the design process would change with IGAIs. The workshop was led by one of the non-landscape architecture authors (i.e., Jose Guridi), and all the authors and team members in Table 1 participated.

We analyzed the data from the interview transcripts, the workshop notes, and the resulting Miro Board from the workshop using a combination of affinity diagrams [30, 43] and axial coding. We analyzed: (1) How do IGAIs change the co-design process of public spaces with the public? (2) How could using IGAIs harm practitioners, participants, and society? and (3) How do landscape architects envision their interaction with IGAIs?

4 TESTING IGAI TO SKETCH IMAGES OF PUBLIC PARKS

The first stage involved the team learning how to use the software to design simple prompts and evaluate the results. The first step consisted of prompting names of parks in Los Angeles mentioned in the interviews (e.g., Schabarum Park) in combination with images of those parks. After examining the results of prompts and outputs with the Dream Studio software, the second step was using information from interviews that was classified using aspects of the Convivial Public Space Framework [42]: Place, Activity, Features, Emotion, and Sense of Place. From selected quotes, we identified keywords that would serve as the base for the prompt, as can be seen in Figure 1, and combined them with the park mentioned in the interview as the reference image. Finally, we

incorporated specific features of Dream Studio, such as image type, negative prompts, and weights. Figure 2 shows an example of these tests.

The main conclusions from the first stage were that the reference image was a core component of the results, which might have advantages and disadvantages. If the IGAI was going to be used to propose more creative options, having it hone the image based on the reference images might not be the best alternative. Additionally, to use the IGAI to co-design with participants in real-time, reference images could constrain their contributions in at least two ways. First, when a reference image could be complex to obtain or unavailable, and if the systems rely too much on it, the results might not be the desired ones. Second, images could influence participants, reducing the options space. From these results, the second stage was planned.

The second stage consisted of using the interviews to prompt the system without a reference image. To do so, the team operationalized the interview information in four features for the prompts: Atmosphere (i.e., Overall sense of place and components that make up the background), Program (i.e., Main activities happening in the image), Features (i.e., Key elements that make up the atmosphere and program), and Context (i.e., location of the image). For example, from interview 3, the following elements were constructed in step 1, previous to prompting the image:

- **Atmosphere:** A dog park, a big tree alley leading to an open space lawn where people can play with dogs and jog around.
- **Program:** People jogging and walking dogs. People of Hispanic origin sit together and chat.
- **Features:** Clean wooden or stone benches for people to sit, proper signage for dog park regulations, and Mexican food vendors selling tacos.
- **Context:** Los Angeles.

The main conclusions from the second stage (see example of Figure 3, in which more iterations and detailed prompts are needed to achieve images that resemble the team's vision. To build the prompts during participatory workshops, practitioners would need more expert knowledge on using the software and quickly translating stakeholders' preferences into detailed prompts. A potential solution would be to prepare purpose-made reference images based on other sources of information before the co-design workshops.

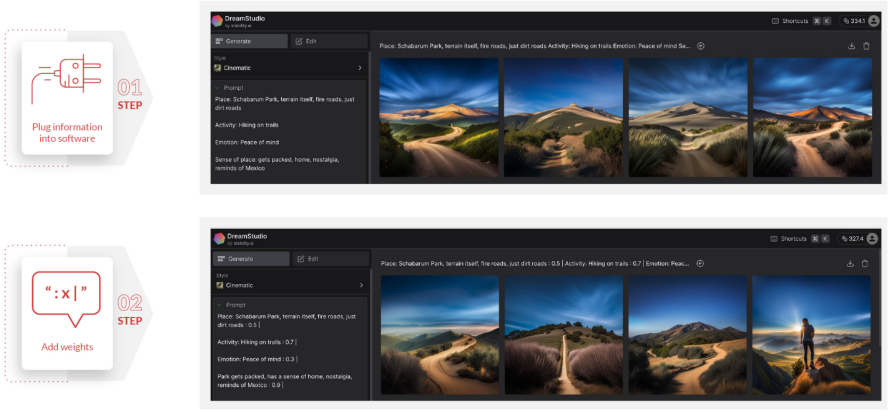
After the two stages, short and specific trials were conducted to understand further the features and the potential use of constructed reference images (i.e., purposely designed images through Photoshop to serve as the reference image). These trials did not use data from the interviews in LA but synthetic prompts to explore the potential of constructed reference images and prompting features. Hierarchy (i.e., the weight of different elements in the prompt) and placement (i.e., location of the elements) were helpful features to achieve images closer to the team's vision. Constructed reference images in Photoshop also improved the image's accuracy, but it could override some specifications made through the prompt regarding hierarchy and placement. Finally, we tried specifying the dimensions of the elements (e.g., the size of a pool and the height of a tree), but the trials were unsuccessful.

5 REFLECTIONS ON THE USE OF IGAI

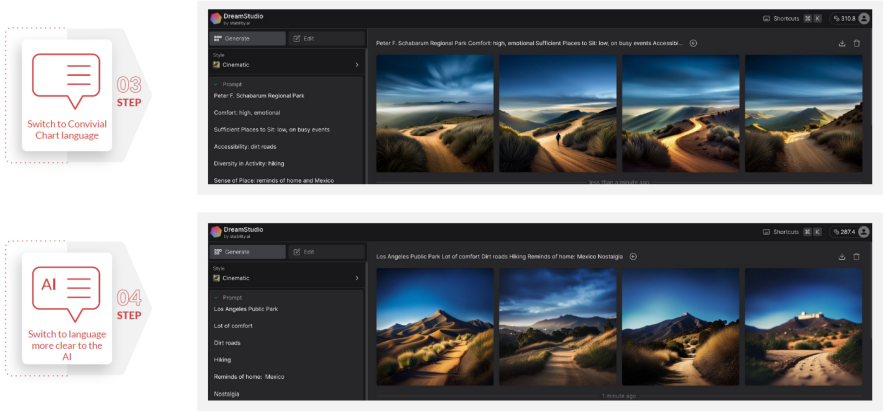
We clustered three reflection topics from the analysis of the notes, interviews, and the workshop: Opportunities, Risks and Challenges, and Features and Requirements. Here, we discuss the main conclusions and further venues of inquiry for each of them.

5.1 Opportunities

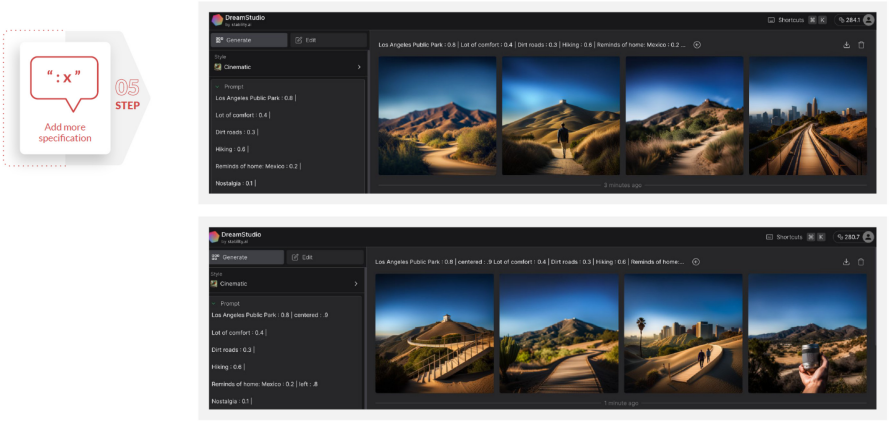
We distill three interrelated areas of opportunities due to the enhanced translation of words into images by IGAI: multiplicity, engagement, and efficiency. Figure 4 summarizes the reflected relationships between the three areas



(a) Stage 1 - Steps 1 and 2

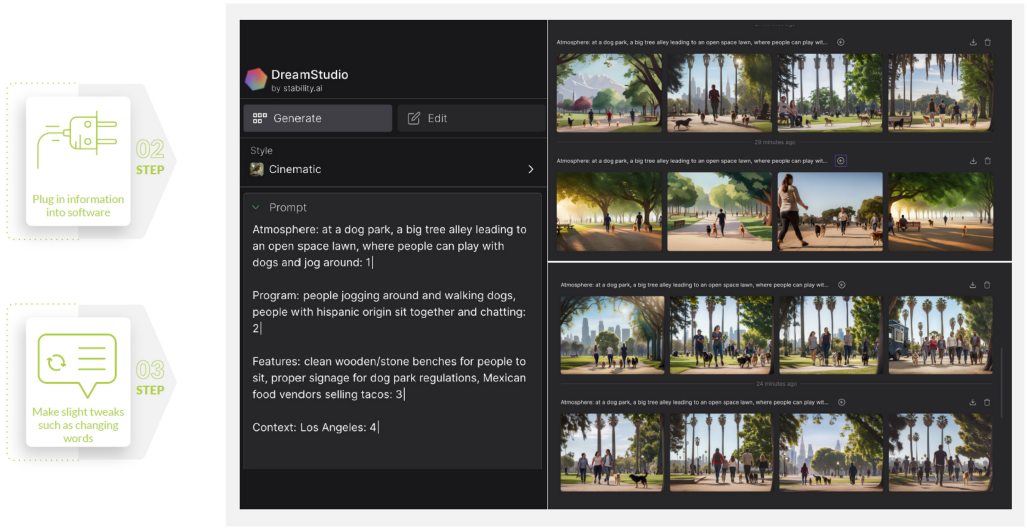


(b) Stage 1 - Steps 3 and 4

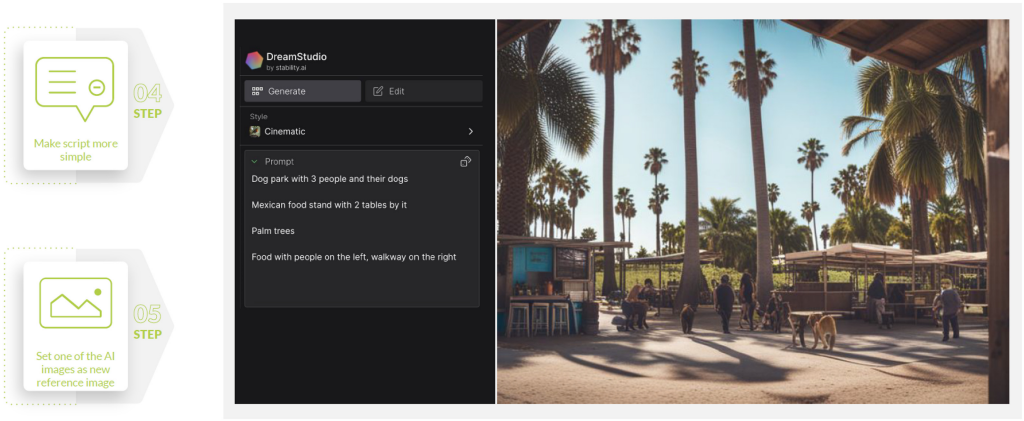


(c) Stage 1 - Step 5

Fig. 2. First stage of trials.



(a) Stage 2 - Steps 2 and 3



(b) Stage 2 - Steps 4 and 5

Fig. 3. Second stage of trials.

and how the enhanced translation would influence each of them. Dashed lines represent relationships without the IGAI, which shows how multiplicity and engagement can foster one another.

5.1.1 Multiplicity. Using IGAI can increase multiplicity in the exploratory stages of the design process. Being able to generate multiple images in a matter of seconds with a system trained with massive datasets broadens the amount of alternatives for design ideas. Depending on the stage of the design process, multiplicity could take different shapes. In the initial stages, designers could use IGAI to generate images from the status quo mainstream to identify trends. Similarly, using the style feature, IGAI could offer exemplary cases based on specific authors or schools of thought. Since exploration stages are more divergent, even if the images make no sense, they can prompt reactions in the designer, which leads to creative ideas and concepts. In sum, IGAI can work as a toolbox of choices that allow the designer to make new mental connections from a broader source of inspiration.

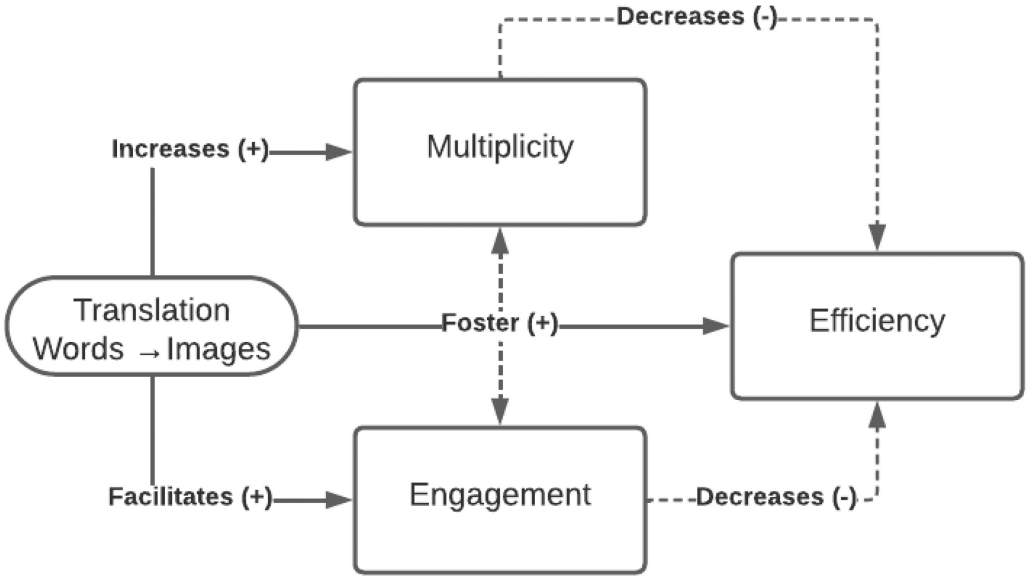


Fig. 4. Opportunities of IGAI.

In advanced stages, IGAI could generate more options based on feedback from stakeholders, potentially reducing the assumptions in the decision-making process. Landscape architects and policymakers must make implicit and explicit decisions that hone stakeholders' preferences and propose a manageable set of options. Using IGAI could allow practitioners to reduce the amount of assumptions and generate and analyze more options. Similarly, the design of public spaces might need to optimize for different conflicting values, which might be hard to test. IGAI could enable practitioners to try options and seek more complex alternatives that reconcile values or solve trade-offs differently. Increasing multiplicity, IGAI could improve Generative Urban Design models by incorporating qualitative performance objectives such as local characters, design aesthetics, and contextual integration [21].

5.1.2 Engagement. Using IGAI can enhance how practitioners interpret stakeholders' preferences. People usually struggle to vocalize specific requirements or ideas unless presented with support material, usually in visual forms [21, 34]. Designers could use IGAI to support participants who do not know the lexicon of landscapes and design since it could help people visually explain things they tacitly know or recognize. Similarly, by generating multiple support materials quickly or enabling new forms of participation, practitioners could generate more personalized approaches and reach diverse stakeholders [34].

Using IGAI to engage stakeholders can enrich the relationship between practitioners, stakeholders, and the general public. Using IGAI could help advance understanding of the relationship between landscape and public space since co-editing the visual outcomes can ground the verbal responses and allow deeper conversations. Using IGAI can also expedite responses to stakeholders or even make it instantaneous, which increases engagement and makes practitioners more accountable. Similarly, using IGAI can help make the design process less of a black box and help stakeholders understand how decisions are made and how inputs connect to the final design of the public space.

5.1.3 Efficiency. Using IGAI can decrease the time, team size, and resources required to generate design alternatives and interpret stakeholders' requirements. Usually, designers need teams to manually build models, sketches, and prototypes from stakeholders' input, constraining the number of iterations and alternatives they

can produce. However, using IGAI makes processes cheaper and less labor-intensive by replacing or facilitating tasks. Thus, similarly to Generative Urban Design tools, IGAI can make qualitative exploration more efficient and enable a broader set of options [21, 27, 47].

Increasing engagement and multiplicity will usually increase costs and requirements to analyze inputs and generate appropriate responses. By contributing to efficiency, IGAI can compensate for the increased requirements of the processes, keeping efficiency constant or even growing it. An exciting venue for further research would be quantitatively estimating the relationships between Multiplicity, Engagement, and Efficiency using IGAI.

5.2 Risks and Challenges

We distill two areas of concern about using IGAI in the co-design process: Power imbalances and biases. Both issues are closely related to how the process and the IGAI are governed. Thus, practitioners must design governance structures that acknowledge the implementation of IGAI as a socio-technical system.

5.2.1 Power Imbalances. IGAI can shift power at individual, organizational, and social levels. An excessive focus on increasing efficiency without considering how that would change the role of designers can shift power towards the IGAI, turning humans into system tools. The increased speed and lack of explanations on how the system works might reduce reflection and the capacity to respond critically to the system's outputs. Designers without agency and a critical approach to IGAI could cease co-creation and delegate creativity and decision-making to the system, which could be detrimental to the design process and, more broadly, to society. At an extreme, if designers cease to add value to the process, they could be replaced entirely.

However, participants did not think the pessimistic automation scenario would happen. They saw that IGAI would probably act as a new tool just like other computer-aided design software had in the past (e.g., Photoshop, AutoCAD, Autodesk, Rhino 3D). They believe public spaces are complex systems in which the engagement with the public and the visual material are only one piece that an interdisciplinary team uses to design the space. The main challenge will be that designers must approach these systems more critically, allowing them to challenge IGAI, retain agency, and not believe that the outputs are objective or sound without questioning.

At a broader level, widespread use of IGAI in the design process might increase the power of corporations and most advanced countries. Practitioners hardly understand how IGAI is developed or the data used to train them. Owners of the technology and the regions in which they are created can become even more preeminent, and new ways of digital colonialism might be enabled.

5.2.2 Biases. When using IGAI in contexts with underrepresented communities, the system's outputs are likely biased. If training data do not adequately incorporate and balance the context-specific information, the system will likely produce results biased towards dominant cultures or reinforce existing stereotypes. Practitioners have their own biases when engaging in co-design processes. However, IGAI might reinforce them and cover the results with an illusion of objectivity or absence of bias if practitioners are unaware that machines are not objective per se.

Biased outputs could generate negative impacts in different ways. When using IGAI to engage the public, stereotyped images could harm participants and negatively impact participation. This is particularly relevant when engaging with marginalized communities, such as immigrants, since it could harm their sense of belonging [19, 23] and contribute to further marginalization. Similarly, massively aggregating images to train the system could lead to excessively standardized images. IGAIs might generate average options that cannot represent the context's specificities or the stakeholders involved.

5.3 Features and Requirements

Dream Studio was too generic and did not address the specific needs of landscape architects when designing images. Practitioners need the ability to tailor pictures in a more granular way, being able to change specific

elements in specific positions. Regenerating the image with each prompt and being unable to edit only specific pieces of the composition was an important barrier to achieving satisfactory results. Additionally, reference images did not always help precision, and how they would help was obscure.

In terms of interaction, more interactivity was required. The team missed the feature of being able to ask the system questions about the image to understand the underlying assumptions of the composition. This feature is crucial to assessing biases and which values are maximized when generating the output. Practitioners envisioned a system that emulated what happens in an architect's studio, where iteration comes from the discussion about the underlying themes of the composition.

Landscape architects require more control to input context-specific elements. Since the training data is unknown, information about the representativity of specific places and populations and the ability to incorporate data (more than a reference image) from the particular context is relevant to address participants' needs and reducing biases and stereotypes. Combined with granularity, practitioners also mentioned the need to input references for specific elements (e.g., the style of a bench or types of trees) and not only a general reference image.

The core need on the practitioners' side is fostering critical approaches to leverage IGAI benefits. Design is about reacting to stimulus and translating that into complex solutions that are embodied in public spaces. IGAI provides a new stimulus source and a tool that enables faster iterations. Still, if designers delegate their agency, it could end up harming those who should be beneficiaries of the spaces.

6 CONCLUSIONS

Overall, this case study provides a context for examining the ethical use of IGAI in the design processes of public spaces through participatory processes. Using Dream Studio as a design probe, we uncover opportunities for multiplicity, engagement, and efficiency that could outweigh the potential challenges of IGAI if used with greater reflexivity and to foster a broader engagement with marginalized populations. We believe the challenge comes by assuming that such technologies are objective, accurate, or factual. Instead, we see that the IGAI can be a tool to make explicit and counter structural human biases to create more inclusive and sustainable public spaces.

Moving forward, we think several venues should be addressed in future research. First, broader empirical work done with practitioners and the public could uncover more specific features and potential pitfalls of using IGAI to co-design public spaces. Second, as research on GenAI risks and challenges moves forward, more work must be done on best practices to prevent harm when using IGAIs in co-designing public spaces. Third, our research focused on the designers, while other actors, such as government officials, also play significant roles in using IGAI for public engagement. Future work could address the organizational dynamics when implementing GenAI in participatory processes.

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