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Paradigmatic design thinking: how generative AI changes the role of human designers

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ABSTRACT: Engineering design has recently undergone a paradigm shift led by generative artificial intelligence (AI). The Generative Design (GD) paradigm utilizes generative AI tools (e.g., large language models) to define the objective space and computationally exploit the design space. This is a drastic shift from the roles of human designers in the Traditional Design (TD) paradigm which consists of manual design-objective space co-evolution, and has created a research gap for Generative Design Thinking (GDT): how a designer thinks and cognitively approaches the design process during GD. To fill this gap, we propose the Paradigmatic Design Thinking Model which uniquely defines design thinking as situated within three factors (Design Cognition, Design Tools, and Design Methodology) and use it to explain design thinking in two paradigms: Traditional Design Thinking and Generative Design Thinking.

KEYWORDS: design cognition, creativity, design theory

1. Introduction

Engineering design is a unique mental activity (Lawson, 1997), and a major branch of design research has been to study *design thinking* and *design cognition*: the cognitive processes, personality traits, knowledge base, and previous experiences of human designers (Hay et al., 2017). However, design researchers have not yet reached a consensus on what design thinking and design cognition each precisely refer to, and these terms are sometimes used interchangeably (Cross, 2023). Adding to the confusion, researchers from non-engineering design fields have widely applied design thinking in non-design contexts (Dorst, 2011; Liedkta, 2015). We argue that a key reason that design thinking and design cognition lack a uniform definition is due to the inherent complexity of the design process, which stems from several factors. First, what differentiates design from non-design tasks is that variables in design problems are "ill-defined" (Simon, 1973), or, "wicked" (Rittel and Webber, 1973), and the goal of the human designer during exploration (i.e., after iteratively exploring and defining the problem space has traditionally been to drive the co-evolution of the design and objective spaces. This occurs as the human iteratively re-frames variables to propose new artifacts in the design space and subsequently evaluates them in the objective space, thus providing the designer with more information on how to explore the design space during the next iteration (Maher and Poon, 1996; Dorst and Cross, 2001). Second, design is a situated activity which is heavily influenced by the context of the problem being solved, the methodology the designer uses to solve it, and the tools they use physically/digitally represent design artifacts (Gero and Kannengiesser, 2004; Gero and Milovanovic, 2020). We embrace this complexity in the present paper as the differentiating factor between the terms design thinking and design cognition: the former refers to the higher-level cognitive activity of a designer while solving situated design problems, specifically, how one thinks in relation to design methodologies, design tools, and: design cognition, which consists of the lower-level cognitive behaviors which occur solely in the mind of the designer (a similar distinction between the two terms is made in Gero & Milovanovic, 2020).

However, design is situated within changing concepts. A paradigm shift driven by generative artificial intelligence (AI) has recently occurred in the methodologies and tools being used to solve engineering design problems (Demirel et al., 2023; Li et al., 2024; Regenwetter et al., 2022). Specifically, various types of generative AI algorithms (e.g., genetic algorithms, variational autoencoders, generative adversarial networks, large language models) used as tools for engineering design uncover new methodologies for the designer to work through the design process. In what we term the Traditional Design (TD) paradigm, the co-evolution of the design and objective spaces during exploration which follows problem space definition is manually driven by human designers manipulating variables in the design space (i.e., an abstract representation of each possible design artifact to a problem) to create artifacts and subsequently evaluating artifact performance in the objective space. In turn, this informs the designer during the next iteration of design space exploration (Maher and Poon, 1996; Dorst and Cross, 2001). We call this exploration methodology Forward Design (Figure 1): working from the design space to the objective space. A key role of designers is to re-frame variable configurations to generate new ideas in the design space, which may be executed by various mental heuristics/strategies (e.g., framing, brainstorming, design-by-analogy; Cross, 2005; Lawson, 1997) and/or physical/digital tools (e.g., sketching, prototyping, computer-aided design). However, the use of generative AI tools in the Generative Design (GD) paradigm changes the role of the designer and the methodology they employ during exploration. This new Backward Design methodology which occurs when the designer works from the objective space to the design space is enabled only when using generative AI tools which offload human design space exploration by computationally exploiting each possible solution after being given a human-defined goal(s) and constraints in the objective space (and the prerequisite functional requirements and parameter ranges in the problem space). Thus, there is a drastic shift in the roles of human designers and their cognitive behaviors between different paradigms (e.g., TD vs. GD).

Previous work does not always distinguish between the design and objective spaces. For instance, Maher and Poon (1996) referred to the design/solution space as consisting of 1) each possible design artifact and 2) each artifact's performance. We believe that this distinction between the design space (each possible design artifact) and the objective space (each artifact's performance) is helpful to consider when contrasting traditional design exploration to AI-driven exploration enabled by generative AI (Figure 1). The former is driven by the human iteratively creating new artifacts in the design space and evaluating them in the objective space. However, generative AI algorithms offload design space exploration and allow the human designer to drive exploration and design-objective space co-evolution by iteratively defining and adjusting performance goals/functional requirements/variable ranges in the objective space for the AI.

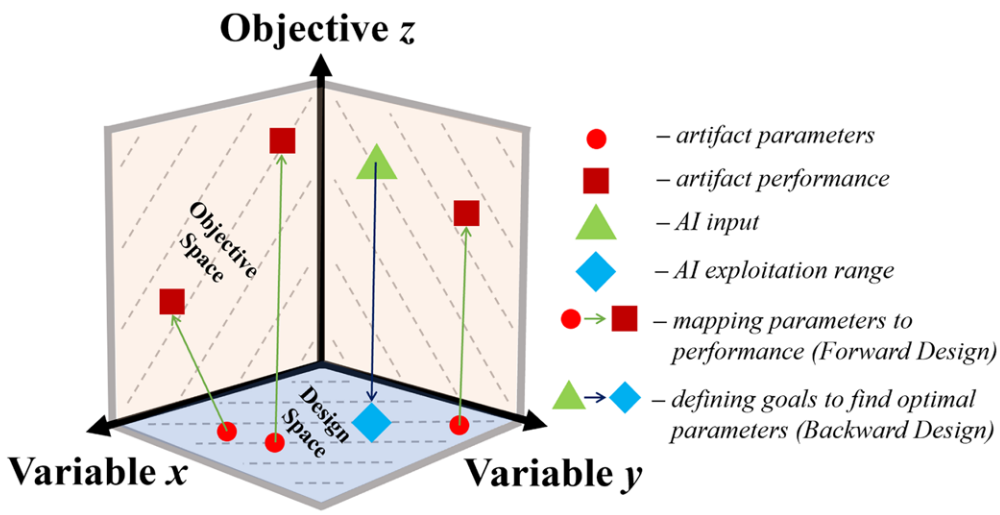

Figure 1. In Forward Design exploration, the designer iteratively re-arranges variable parameters (Variables *x* and *y*) in the design space and evaluates artifact performance in the objective space (Objective *z*) as they drive space co-evolution. In Backward Design exploration, the human designer collaboratively co-evolves the spaces by first defining the goals/requirements/ranges in the objective space for the AI to reference while it exploits the design space to find the optimal parameter combinations

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The application of generative AI (particularly LLM-based techniques) to engineering design is relatively recent. Previous research on design thinking and design cognition was conducted in the context of other paradigms, chiefly TD (though not with the "traditional" prefix) and Parametric Design (PD; sometimes referred to as Digital Design; Oxman, 2006, Oxman, 2017a; Oxman, 2017b). Thus, the rise of a Generative Design paradigm creates a research gap for what we term Generative Design Thinking (GDT): how a designer thinks during GD. More specifically, GDT can be considered a designer's thinking situated in a Backward Design methodology and using generative AI tools. Like design thinking in previous paradigms, GDT is also situated in relation to the designer's individual differences in design cognition (i.e., cognition, personality, and experience).

2. Paradigmatic design thinking framework

To address the need for a definition of Generative Design Thinking (GDT), we propose the Paradigmatic Design Thinking Model (Figure 2). Our goals for this model are to 1) visualize the system of relationships between design cognition, design tools, and design methodologies; 2) describe and explain Traditional Design Thinking (TDT) and Parametric Design Thinking (PDT) based on this framework; and 3) define Generative Design Thinking based on the framework which describes TDT and PDT. Our model takes a novel approach by defining design thinking based on three factors that design is situated within: a designer's cognitive behavior and previous experiences (Design Cognition), the tools that they use to create a design artifact (Design Tools), and the role of the human during design as determined by the direction they take during design-objective space co-evolution (Design Methodology).

There is a natural relationship with design tools and methodologies in that tools "unlock" certain methodologies for designers to use, e.g., generative AI tools allow one to do Backward Design (Figure 2, *f*). In turn, design methodologies imply the use of certain design tools by providing the direction for the designer to take when driving the co-evolution of the design and objective spaces: forward from the design to the objective space using TD or PD tools, or backward from the objective to the design space using GD tools (Figure 2, *e*). We define Design Paradigms as the bidirectional relationship between design tools and design methodologies, and we highlight three Paradigms: TD, PD, and GD. Human errors and the slow speed of manual TD practices spurred the development of parametric and computational based tools to automate some design tasks to aid the human designer's decisions (Oxman, 2006; Caetano et al., 2020). In turn, the technology which underlies the current GD paradigm evolved from the tools used in PD to further automate tasks by offloading some decisions (usually in exploring the design space) to the AI (Mountstephens and Teo, 2020). In this way, new design paradigms evolve from previous paradigms and are influenced by previous technologies and practices.

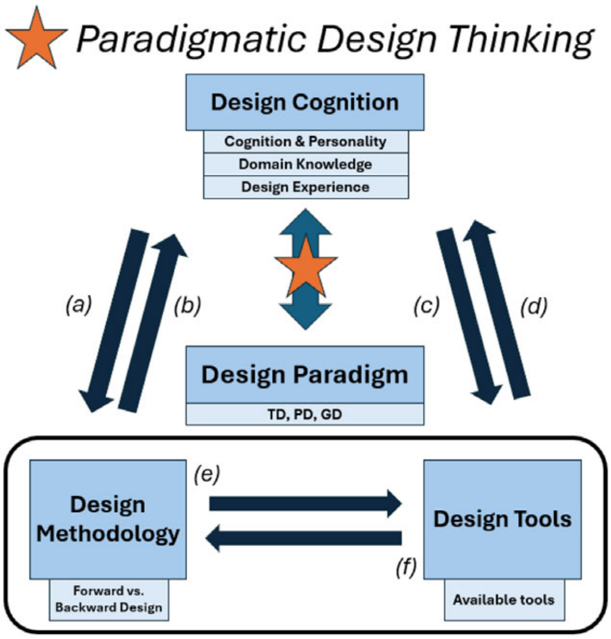

Figure 2. The Paradigmatic Design Thinking Model which describes design thinking as being situated in three factors: Design Cognition, Design Tools, and Design Methodologies

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There are also bidirectional relationships between Design Cognition and the methodologies and tools that make up Design Paradigms. Forward and Backward Design each require the designer to take different roles and complete a different set of tasks as they drive design-objective space co-evolution. Thus, each methodology will imply a set of relevant cognitive behaviors in the same way the methodology implies the use of a set of design tools (Figure 2, *b*). In turn, individual differences in design cognition will influence how well one is able to carry out design methodologies (Figure 2, *a*). For example, a designer who is unable to generate many design alternatives will conduct Forward Design differently than a designer with high ideation skill. Design Tools create the physical and/or digital design solution, and thus mediate the designer's cognitive behaviors (Figure 2, *d*). Finally, individual differences in design cognition influence the use of tools just as they influence the use of methodologies (Figure 2, *c*).

We will demonstrate our model in this paper with two case studies which illustrate Paradigmatic Design Thinking in one of the identified design paradigms through a review of relevant literature. The literature that we present in the current study is not a comprehensive view of the field and the papers reviewed were not systematically collected. Instead, we first opted to review and describe the findings of illustrative and highly cited papers with the keywords design thinking and/or design cognition in the context of TD. We detail the role of key design thinking concepts to provide a deeper description of TDT based on the underlying mechanisms. We then leverage the concepts and mechanisms at the core of TDT as a structure for explaining GDT, specifically how design thinking and design cognition concepts change when adding generative AI to engineering design. In the current paper, we specifically focus on the role of design-by-analogy as a heuristic/strategy and one example of the design methodologies for generating creative ideas during the design ideation phase, and how expertise and previous design experiences influence how designers behave.

3. Traditional design (TD) and traditional design thinking (TDT)

3.1. Design methodology and heuristics

A central component of the types of design problems that are solved in literature referencing the Traditional Design process using the Forward Design methodology is that the initial problem representation (or, "frame") does not imply a clear and useful solution (Kelly and Gero, 2021). Thus, the role of the designer and overall goal of design thinking is to re-frame the old problem representation into a new one which can be explored to find a potential solution. Novelty and usefulness (i.e., utility) are the central characteristics of creativity; an idea must be both unique and relevant to the problem situation to be judged as creative (Runco and Jaeger, 2012). Two different ways of solving creative problems are via insight or incrementally. Creative cognition researchers have spent much effort studying insight, a phenomenon in which a previously unknown solution to the problem is instantaneously recognized by the problem solver. This recognition is usually accompanied by a feeling of surprise, and is often referred to in literature as an "Aha!" or "Eureka!" moment. The central mechanism for achieving insight is a perspective shift leading to the restructuring of the problem conceptualization that one previously could not find a solution to; there cannot be insight without restructuring (Abraham, 2020, pg. 67).

One of the key cognitive mechanisms for generating ideas to reframe a flawed problem concept and achieve insight is to use an analogy. Though traditionally studied in the fields of psychology and neuroscience, using analogies is also a key concept in engineering design under the terms design-by-analogy or sometimes *Synectics* (Cross, 2005, pg. 51) as a heuristic generating ideas during the conceptual ideation phase. Making novel associations between different concepts is useful for generating novel ideas, and analogies allow one to make a unique association by connecting semantically distant knowledge concepts by overlaying (*mapping*) the rules and structure of one concept (the *source*) onto another (the *target*; Holyoak et al., 2024; Abraham, 2020; pg. 118). The source and target concepts are mentally represented and stored within semantic networks in the designer's memory, and the semantic distance between the source and target is often considered key to determining the effectiveness of the analogy being made. Specifically, some researchers argue that there is a positive correlation between the novelty (but not necessarily usefulness) of an idea generated via analogy and the semantic distance between the source and target concepts; the further the distance, the more novel the relation between them (Vendetti et al., 2014; Holyoak et al., 2024). However, there is an opposing body of empirical evidence which suggests that not only are nearby sources potentially

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more beneficial to creativity than far ones (Chan et al., 2015), but also that there are other factors which mediate the usefulness of inspirational external information.

One study (Chan et al., 2011) analyzed data from 153 senior level (majority mechanical) engineering students to test the influence of three characteristics of inspirational content: analogical distance (near vs. far), commonness (more vs. less common), and representation modality (picture vs. text). Ideas were evaluated for solution transfer (number of features leverages from experimental stimuli), quantity (number of alternative design solutions generated), breadth of search (amount of solution space explored), quality (according to a predetermined rubric), and novelty (in relation to the other solutions). The authors found that the "optimal example" which was related to increased novelty in subsequent design solutions was one that exposed the designer to an idea with far analogical distance and low commonness to the original problem representation. In summary, stimuli which are helpful for creative ideation are those that are semantically distant and novel to the original flawed representation.

3.2. Design cognition

Design is heavily influenced by a designer's previous experiences, particularly those related to engineering design. The key distinction in design experience literature is between novice/beginner and expert/informed designers (Crismond and Adams, 2012), and researchers have taken a wide range of approaches for studying novice and/or expert designers. One of the most common methods of studying designers, design thinking, and design cognition is protocol analysis (or, the think-aloud method) which directly collects and analyzes verbal behavior of designers solving design problems (Gero and Milovanovic, 2020). In Cross' (2004) review of design expertise research, he divides the approaches that researchers take to study expertise into three categories: 1) comparing the performance of expert vs. novice designers; 2) studying the behavior of expert designers; and, 3) studying the behavior of outstanding designers. Key differences between expert and novice designers spent more time in the problem definition stages of the design process (Atman et al., 1999), often because they became fixated on gathering more information than needed to begin exploring the design space (Christianns and Dorst, 1992). During design-objective space co-evolution following problem definition, novice designers also displayed several different tendencies than those with higher experience. For instance, Ahmed et al, (2003) studied the behaviors of industrial designers and found that newer practitioners heavily relied on trial and error techniques during design space exploration, where ideas were sequentially realized and evaluated before generating the next idea. However, more experienced designers were able to frame and evaluate their design decisions before implementation, thus avoiding unnecessary effort and allowing additional time for driving design-objective space co-evolution. In summary, expert designers spend less time spent in problem definition, and more actively engage in problem framing which prompts them to focus on the solution instead of the problem variables. Additionally, this expertise is even more valuable within a domain where one can leverage previous experience to swiftly identify a potentially useful problem frame.

To illustrate the influence of design cognition on the use of heuristics, we highlight that several studies have found that the experience of the designer mediates how they use analogies. One study (Ball et al., 2004) differentiated between schema-driven analogies ("recognition-primed application" of design knowledge and previous experiences) and case-driven analogies (intentional application of prior design solutions), and their results found that experts engaged in the former more than the latter and novices did the opposite. Expert designers were able to abstract the rules from their previous experiences (i.e., the source) and apply them to the target problem. However, novices lack the sufficient experience to do this and instead rely on a smaller sample of concrete sources to map to the target. In other words, effectively using analogies as a heuristic depends on the previous experiences of the designer as it expands their sample of semantic network source nodes to draw inspiration from. Another study (Ozkan and Dogan, 2013) found that expert designers generally drew inspiration from far sources (i.e., conducting a "mental leap;" Holyoak and Thagard, 1997), while novices preferred "mental hops," i.e., sourcing analogies from concepts in nearby semantic networks (Ward, 1998). Overall, research suggests that expert designers (compared to novices) are able to draw on a larger base of previous experiences, from which they have abstracted general rulesets which can be applied to target problem domains, which tend to be further from the sources that they activate.

Summarizing in the terms of the Paradigmatic Design Thinking Model (Figure 2), TDT is situated within the TD Paradigm which takes the Forward Design methodology, prompting the designer to

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take the direction of moving forward from the design space to the objective space while driving co-evolution. All progression is attributed to the human designer who makes all decisions and manually completes all design actions. A unique characteristic of a major class of design problems described in studies on design thinking in Forward Design is that they must be solved by novel and useful ideas (Kelly and Gero, 2021), i.e., creative ideas (Runco and Jaeger, 2012), often because designers must begin to solve these "wicked" problems without knowing all of the variables (Simon, 1973; Rittel and Webber, 1973). Thus, progress towards a creative design solution is made by the human designer as they generate new representations of the design and/or objective spaces. One of several heuristics for generative new representations is via analogies, where one maps the rules of a source concept onto a target concept to make a novel association. A designer's previous experience, i.e., Design Cognition, is a determining factor of how effective they are in using analogies to solve design problems; in short, more experiences give the designer more sources across a wider range, thus increasing the chance of finding a novel association.

4. Generative design (GD) and generative design thinking (GDT)

In this section we consider how differences between Backward Design and Forward Design change the process of re-framing a flawed problem representation to achieve insight into a new and useful one. Design-objective space co-evolution in Backward Design is driven from the objective space to the design space. Specifically, the human designer's mental representation of the objective space is computationally represented for an AI agent to use as a guideline as it exploits the full design space instead of exploring a subset of the design space as the human does in TD. The human designer generally takes a higher-level role by iteratively generating new representations of the objective space which a lower-level "assistant" AI agent will reference as it exploits the design space. The designer does not know all relevant information when solving "wicked" design problems, and thus, the original representation of the objective space offered to AI may not achieve a solution which is useful to the problem at hand. A recent study found that the human designer's goal in this case then shifts to re-framing the objective space to guide the AI towards generating a more novel and/or useful set of potential design solutions (Saadi, 2024).

In summary, the Backward Design methodology in the GD paradigm is made available to designers using GD Tools which allow them to move backward from the objective space to the design space as both the human and the AI drive co-evolution. However, there is a dearth of research on how human designers may be creative during the GD process. In creative Forward Design, the designer manipulates the variables which make up the design space. However, humans in GD do not always directly change the variables and instead mentally represent the higher-level objective space. We conclude the paper with a specific example of using analogies in TD and describe how analogies may be used in GD as a strategy for creatively re-framing the human designer's representation of the objective space.

5. Design-by-analogy in TDT vs. GDT

Aladdin is an open-source CAD/CAE platform developed by the Institute for Future Intelligence which enables designers with traditional and generative design capabilities for creating and analyzing solar energy structures, e.g., solar farms (Xie et al., 2023; Figure 3). This platform allows design researchers and educators to develop project-based learning modules for students to complete and provides access to a fine-grained sequential log of each action made by the user. We use an example in the context of Aladdin as it provides a readily accessible and free to use platform for testing differences in analogy use (or other heuristics) between TDT and GDT.

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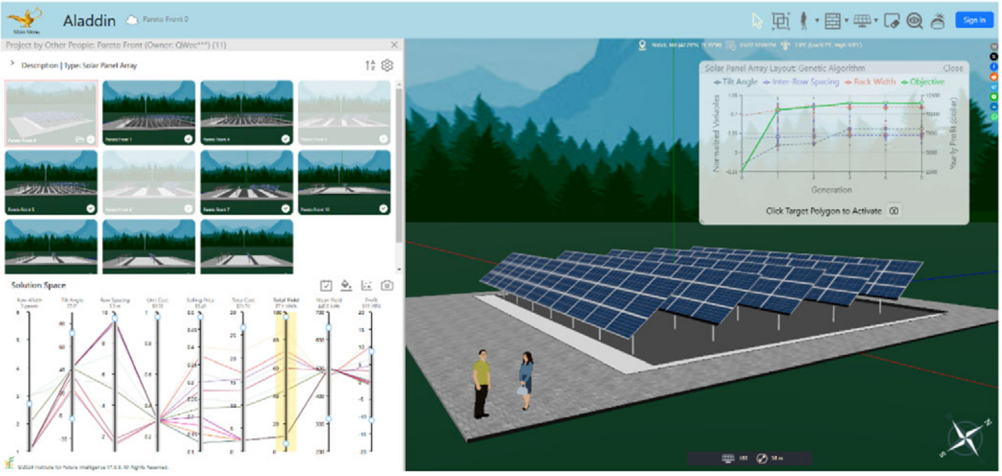

Figure 3. Aladdin allows the user to design, simulate, and analyze the performance of solar energy structures, e.g., solar farms. Equipped with generative design capabilities, Aladdin's interface enables quick multi-objective comparison between a set of different designs

An analogy that a designer may consider while re-framing the design space (consisting of the inter-row spacing, pole height, panel width, etc.) in this context is to map the rules of a crop farm (the source) onto the design for a solar farm (the target). The designer may choose to map "rules" of crop farming which suggest that an efficient layout features narrow, straight rows of crops (in the source, solar panel arrays) with minimum spacing in between the rows. In TD, a designer applying this analogy would manually "plant" solar panel arrays with low width in straight rows and with low inter-row spacing (Figure 4a).

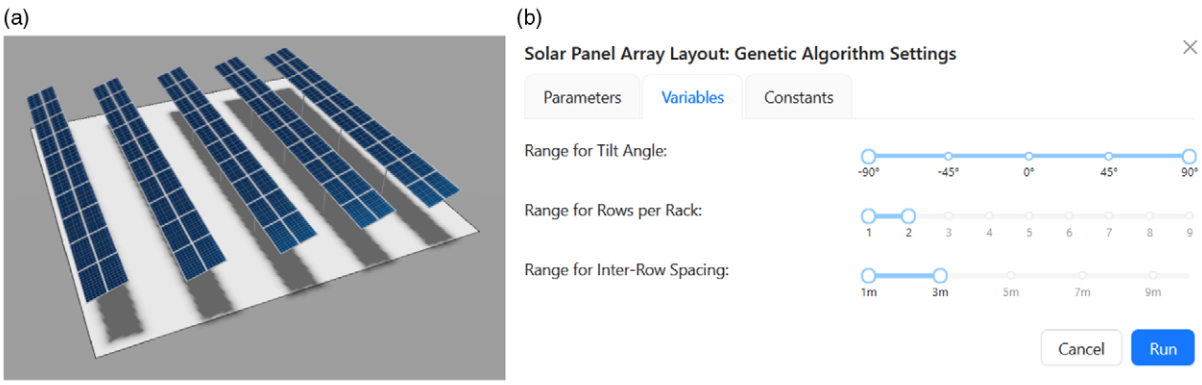

Figure 4. (a, left). In TD, the designer will manually place solar panels and manipulate the variables based on the rules of the analogy source (here, a crop farm). (b, right). In GD, a designer will set the variable ranges for an AI agent to exploit within

However, the designer using generative AI tools does not directly manipulate the lower-level variables. Instead, they begin by defining the objectives and parameter ranges in the objective space (Figure 4b). A designer attempting to use GD to design a solar farm inspired by the rules of crop farming would not manually manipulate each of the variables until the target design resembled the source. Instead, the designer must map the rules of the source onto the target by deciding how to computationally represent the objective space in a way that prompts the AI to generate designs which follow the rules of the analogy source. The "rules" from the crop farm analogy were that the panel rows must be relatively narrow and have minimum inter-row spacing. The designer in GD applying the crop farm analogy must decide the ranges of panel width and inter-row spacing which are not too wide and thus still follow the crop farm rules. The AI agent will then exploit the design space within the defined ranges and provide the designer with a set of optimal designs using the crop farm analogy rules (as the human designer defined them). Thus, applying creative heuristics (here, analogies) in the GD paradigm should require the designer to take a higher-level approach than in TD. In other words, using analogies in GDT is likely different than in TDT.

We describe GDT through the Paradigmatic Design Thinking Model (Figure 2) as being situated within the GD Paradigm which takes the Backward Design methodology enabled by generative AI-based tools. We offer an example of how analogies may differ between TDT and GDT to demonstrate how concepts

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from previous paradigms can be considered in GD, and to explore the potential influence of Design Cognition on the use of GD tools and methodologies.

6. Conclusion

In the present study, we present the Paradigmatic Design Thinking Model (Figure 2) as a new framework to define design thinking as the high-level cognitive behavior that accompanies design situated within three factors: Design Cognition (their cognition/personality/previous experiences), Design Methodologies (e.g., Forward vs. Backward Design), and Design Tools. Design Paradigms consisting of methodologies of tools imply the role of the designer and the relevant Design Cognition concepts. In turn, individual differences in Design Cognition are crucial in determining how the designer thinks and acts while using tools and executing methodologies. We highlighted two paradigms and the accompanying Paradigmatic Design Thinking: Traditional Design (TD) and Traditional Design Thinking (TDT), and Generative Design (GD) and Generative Design Thinking (GDT). To describe TD/TDT, we focused on the use of analogies as a heuristic for generating creative ideas and the role of a designer's previous experiences. Finally, we use this framework to describe GD/GDT and provide an example of how analogies, a well-studied concept from TD, may potentially be applied in GD.

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