Engineering Design Thinking in the Age of Generative Artificial Intelligence

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Introduction

Generative artificial intelligence (AI) algorithms have received attention in a wide range of disciplines and have been increasingly applied in engineering design, including the introduction of generative features to popular CAD software (e.g., Autodesk and PTC) [1], [2], [3]. Generative design (GD) is a computational design technique that utilizes AI algorithms to generate unique outcomes beyond human capabilities [4], [5]. GD methods in engineering apply generative AI to iteratively explore the design space and generate a (set of) solution(s) that satisfy human-defined objectives and constraints [6], [7]. These approaches utilize a range of generative techniques, such as genetic algorithms (GAs), variational autoencoders (VAEs), generative adversary networks (GAN), and large language models (LLMs) [8], [9], [10]. See Figure 1 for a few examples. GAs computationally mimic natural selection by assigning each generated design a *fitness function* to represent how well it reaches the objectives and iterate towards design with higher *fitness* [8], [11]. VAEs represent an unsupervised technique that utilizes an *encoder* to extract high-level features via mapping high-dimension variables into a low-dimensional latent space and a *decoder* to leverage the extracted features to generate new designs [1]. Finally, recent advances in LLM have made it possible to understand natural language and programming code to automatically generate CAD models from texts [10].

In general, generative approaches represent a relatively recent paradigm for approaching engineering design tasks. Parametric design (PD) is an alternative computational-based design paradigm that influenced the development and use of GD technologies [6]. These approaches characteristically use a parametric schema, which visualizes the relevant variables, rule-sets, and parameter interdependencies [12]. This allows the designer to explore the design space by inputting parameters for a potential design, which is then computationally generated [6]. Computational design methods (PD and GD) were developed to address weaknesses in traditional design (TD) practices, which emphasize human cognition and manual (i.e., non-automated and potentially error-prone) completion of design tasks [13], [14]. Human-driven design is the key characteristic of non-computational TD practices, in contrast to computational design methods, which rely on computer algorithms to significantly augment (or, in some tasks, replace) the role of the human designer.

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The use of generative, parametric, or traditional design paradigms significantly shapes the role of the human throughout the design process. For example, the early phases of design emphasize design space exploration, which allows the designer to generate potential solutions by manipulating parameter values and relationships. In the early design stage, a designer using traditional approaches would begin by leveraging their previous experiences and domain knowledge to choose a promising starting point and then drive exploration via human creativity, heuristics, and reasoning. However, human cognition is susceptible to both internal (e.g., design fixation or fatigue [15]) and external biases (e.g., education or socioeconomic status [16]), which may negatively impact design performance. Additionally, the limits of human cognition begin to be tested as the number and complexity of trade-offs, constraints, and user needs that must be considered grows [4], [13]. Finally, traditional/manual design approaches are resource intensive due to the amount of time required for creating preliminary designs, and for manually correcting potential errors made by the human designer during these tasks.

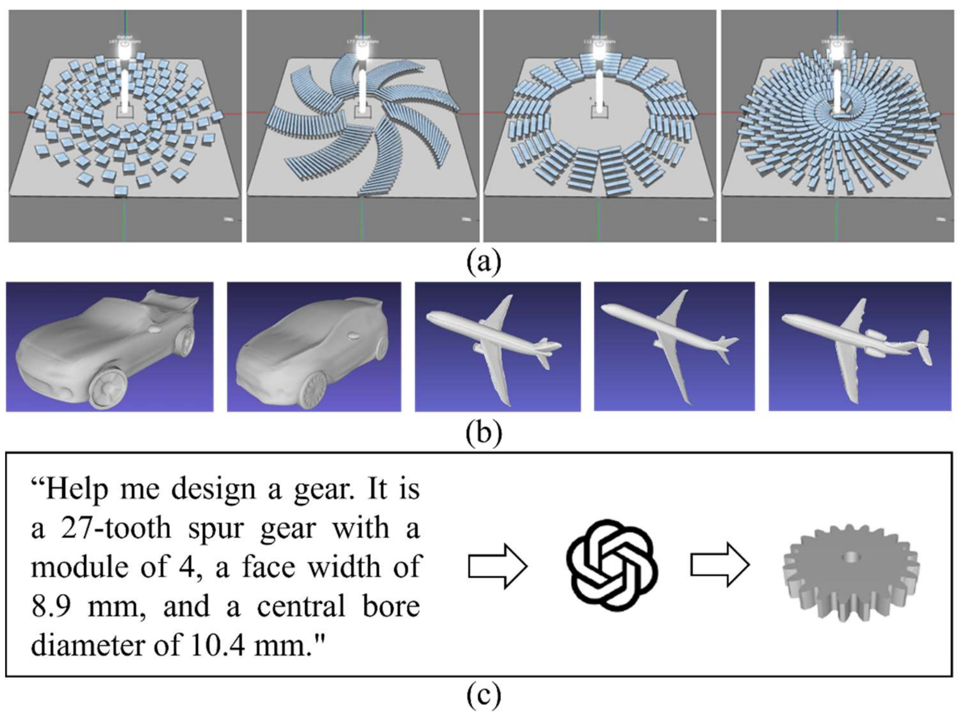

Figure 1. (a) Genetic algorithms exploring possible solutions for renewable solar-energy systems in the Aladdin CAD software [8]; (b) Variational autoencoders for structure-aware design generation [9]; (c) CAD model generation using large language models, such as ChatGPT [10].

Thus, computational design methods (e.g., PD and GD) were developed to overcome those shortfalls mentioned above. A designer using PD/GD is responsible for translating design requirements and parameter interactions into expressions and formulas that may be understood by computational tools, e.g., the parametric schema in PD, and generative AI algorithms in GD [6], [11], [13]. Following this, design space exploration is driven by the designer, who is responsible for inputting the parameters of a potential design to be computationally generated. TD practices prompt a lower-level focus on individual parameters, which are updated manually and sequentially by the designer. However, the focus of the designer during exploration in PD shifts to a higher-level and holistic consideration of each of the relevant parameters and their interrelationships.

In comparison to TD and PD methods, GD methods simultaneously increase the role of computation during design and further change the role of the human designer. Similar to PD, GD requires the designer to computationally define the design space (all possible artifacts represented via parameters and their relationships) and the objective space (performance criteria and constraints). Unlike PD, an AI agent then considers the human-input objectives and (in some algorithms) parameter ranges as it computationally generates and evaluates design artifacts in the design space beyond what is possible for human cognition. Artifacts with optimal performance (i.e., those along the Pareto front) will then be presented to the designer, who must evaluate both the AI-generated designs and the human-input objective(s) and parameter ranges that influenced their generation.

In summary, a designer using traditional approaches will manually manipulate design parameters to create an artifact, and a designer in PD will define the parameters of a design to be automatically created via computation. Both TD and PD follow a traditional design direction that we call *forward design*, i.e., when the designer works from the design space to the objective space. However, GD features a *backward design* direction in which the designer must define the objective space (via the goals and parameter ranges) for an AI algorithm to consider as it explores the design space to determine the optimal arrangements of parameter values to achieve the goals. Thus, a designer using generative approaches must engage in *inverse thinking* when compared to designers in TD and PD (**Figure 2**).

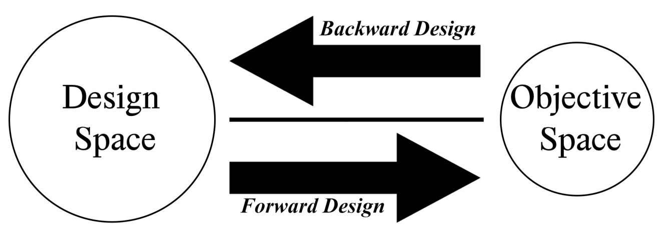

Figure 2. Designers in GD think inversely from the objective to the design space, unlike designers using traditional and parametric methods.

Aims and Significance

The cognitive processes that underly design tasks are generally known as *design thinking* and/or *design cognition*. However, traditional, parametric, and generative design paradigms/processes each require the designer to think and behave in unique ways, i.e., engage in different types of *design thinking*. TD methods are driven by a designer's traditional design thinking (TDT), PD requires parametric design thinking (PDT), and GD must be accompanied by generative design thinking (GDT). Design thinking in TD and PD contexts has received extensive attention from design researchers. However, research investigating the cognitive processes that makeup GDT is in the early stages due to the recent rise of generative AI methods in engineering. The purpose of our research is to trace the evolution of traditional/parametric design methods and thinking styles to clearly define GDT, i.e., the cognitive processes and behaviors that likely play a role in design using generative methods.

Specifically, we argue that the rise of GD methods requires a reconsideration of *design thinking*. However, this is complex due to the wide range of disciplines that have adopted *design thinking* as a term and applied it to their domains in recent years. Based on our observations, *design thinking* is most often used in one of two contexts. First, *design thinking* may refer to the cognitive processes that carry out design tasks. *Design cognition* is also generally used to reference these concepts, and the two terms generally overlap in usage and definition in this context. This approach is often taken by design researchers in the fields of engineering and architecture and has historically leveraged methods and insights from neuro-psychological perspectives [17]. Second, *design thinking* is also considered a philosophy that leverages design concepts (e.g., by adopting solution 'frameworks') for approaching problem-solving [18]. *Design thinking* in this context was championed and propagated by the design consulting firm IDEO, often in information technology and business contexts (e.g., product and service development) [19], [20], [21].

Design thinking in both contexts must be reconsidered in the age of generative AI. First, the use of new design technologies changes the role of a designer and the underlying cognitive processes. Thus, design thinking/cognition researchers should consider extending their studies to investigate designer cognition and behavior while using generative technologies. Second, *design thinking* as an approach to problem-solving must be updated to consider how advancements in design technologies can address changes in the business environment, e.g., increasing market segmentation, which calls for designs that are highly optimized for safety, preference, or environmental concerns [4].

Our work addresses the first context of design thinking and is geared towards defining GDT and highlighting the relevant cognitive processes which will generate impacts in design education and research. The education of future generative designers may be improved by leveraging insights into how designers think and act while using generative technologies, as current GD curricula were developed without these insights [4]. Future researchers may also leverage our insights to directly investigate (e.g., via neuroimaging or other psychological experimental methods), measure, and improve designers' cognition during GD.

Evolving Design Thinking Model

A robust definition of GDT must be grounded in the literature on related design thinking concepts, e.g., TDT, PDT, CT, and ST. We review these topics, discuss the cognitive processes that underlie design activities, and highlight those potentially relevant to GD. These cognitive processes will then be used as a basis for defining GDT. Our review will be guided by the Evolving Design

Thinking (EDT) model (**Figure 3** [22]), a meta-representation to show the evolution of design thinking concepts and their relationships across three levels: Design Technology (i.e., genetic algorithms, machine learning, and other techniques to carry out design), Design Thinking (i.e., paradigm-specific thinking concepts), and Design Cognition (i.e., research on the cognition underlying design activities). Technological development and design cognition research have driven the evolution of TD(T) to PD(T) and from PD(T) to GD(T) [6], [11], [12], [13]. This evolutionary process represents evolving design thinking, a task-relevant set of cognitive processes that both influence and are shaped by design paradigms.

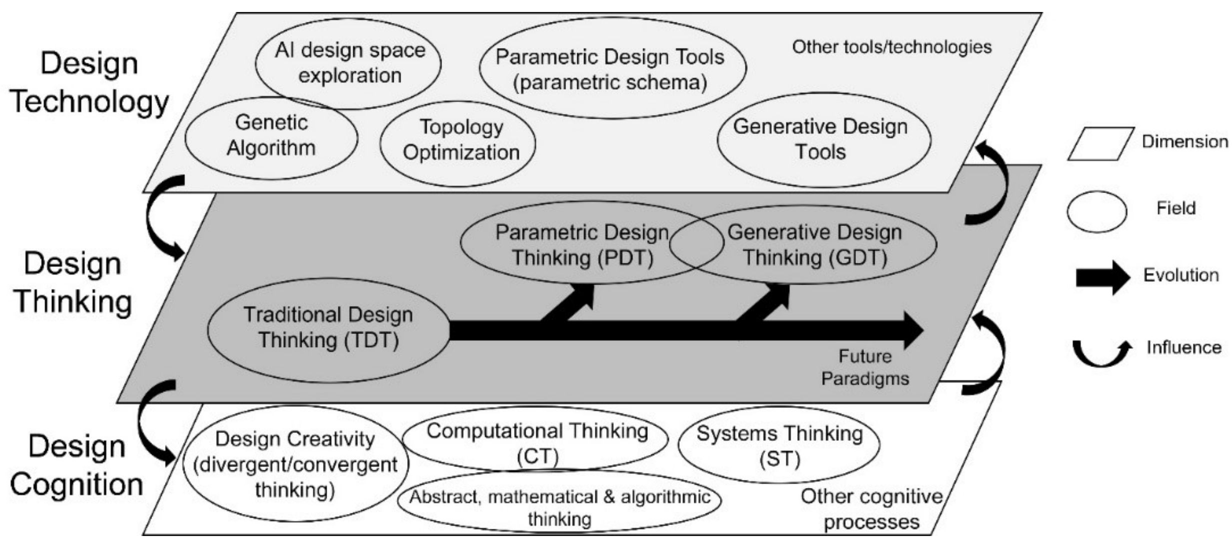

Figure 3. The Evolving Design Thinking (EDT) Model [22].

Research Questions and Proposed Methodology

Our goal is to systematically review design and design thinking concepts in the context of evolving design thinking (TD/TDT, PD/PDT) and highlight trends in previous literature that may inform a definition of generative design thinking. Specifically, we ask two research questions, as shown in **Figure 4**. *RQ1: What cognitive processes are activated by designers using traditional/parametric design?* We plan to systematically review a. traditional design methodologies, b. traditional design thinking, c. parametric design methodologies, and d. parametric design thinking, and highlight trends to show how the processes and tools being used during the design process shape the cognitive process activated by designers. In the context of these insights, we will ask *RQ2: What cognitive processes are activated by designers using generative design?* We plan to systematically review e. the methodologies available for generative design and consider how these methods/tools shape the roles of humans in GD and the underlying cognitive processes. Finally, we will offer a definition of generative design thinking, which considers the influence of design methods/tools on design thinking and traces the evolution of TD/TDT and PD/PDT to GD/GDT.

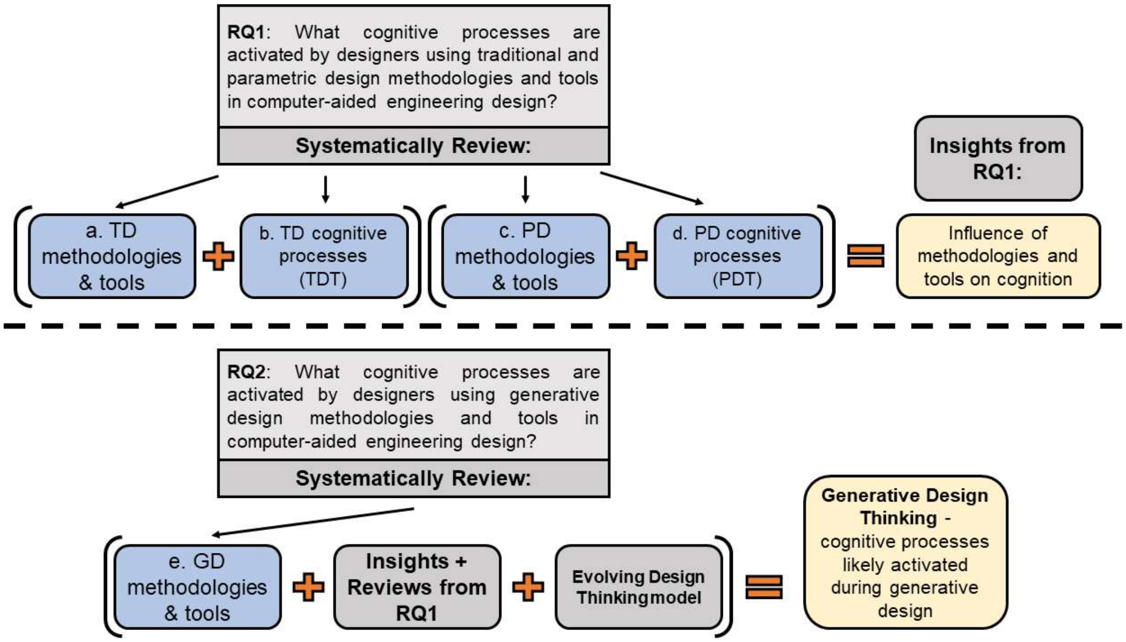

Figure 4. The approach and research questions for the proposed systematic review.

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