COGNITIVE BIASES IN DECISION-MAKING WHEN USING GENERATIVE DESIGN

Thiên kiến nhận thức khi ra quyết định trong sử dụng thiết kế tạo sinh

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ABSTRACT: Generative Design, based on principles of optimization and simulation, is becoming an important tool in contemporary design practice. However, the use of this technology not only poses technical challenges but also gives rise to cognitive biases in designers' decision-making processes. This study focuses on analyzing the interaction between optimization systems in generative design and human cognitive behavior, thereby identifying forms of cognitive bias in order to support designers in recognizing and minimizing these biases, contributing to the more effective application of generative design in practice.

KEYWORDS: Algorithm, Cognitive bias, Decision-making, Generative design

TÓM TẮT: Thiết kế tạo sinh - Generative Design dựa trên các nguyên lý tối ưu hóa và mô phỏng đang trở thành một công cụ quan trọng trong thực hành thiết kế đương đại. Tuy nhiên, việc sử dụng công nghệ này không chỉ đặt ra các thách thức kỹ thuật mà còn làm phát sinh các sai lệch nhận thức (Cognitive Biases) trong quá trình ra quyết định của nhà thiết kế. Nghiên cứu này tập trung phân tích sự tương tác giữa hệ thống tối ưu hóa trong thiết kế tạo sinh và hành vi nhận thức của con người, qua đó chỉ ra các dạng sai lệch nhận thức nhằm hỗ trợ nhà thiết kế nhận diện và giảm thiểu sai lệch, góp phần nâng cao hiệu quả sử dụng thiết kế tạo sinh trong thực tiễn.

TỪ KHÓA: ra quyết định, thiên kiến nhận thức, thiết kế tạo sinh, thuật toán

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1. INTRODUCTION

The rapid advancement of digital technology has profoundly transformed design workflows within the field of architecture. Among these developments, generative design has emerged as a novel approach, enabling the simultaneous generation and evaluation of multiple design alternatives based on algorithms and input parameters. This paradigm shift not only significantly expands the creative space but also redefines the traditional role of the architect—evolving from a direct form-giver into a system designer and decision-maker.

However, along with these benefits, decision-making within a generative design environment has grown increasingly complex. When tasked with selecting from a vast number of system-generated alternatives, architects do not rely solely on data; they are also influenced by subjective cognitive factors. Cognitive biases—defined as systematic deviations in information processing—can considerably impact how design alternatives are evaluated and selected. Particularly within the context of human-computer interaction in generative design, where architects must make decisions from a vast array of outcomes produced by algorithmic systems, these biases may not only persist but can be further reinforced by how humans perceive and assess the results. Therefore, investigating the role of the architect while identifying and analyzing the influence of cognitive biases in generative design workflows constitutes an essential issue with substantial practical significance.

2. THEORETICAL OVERVIEW

2.1. The Concept of Generative Design

According to Ma et al. [1], generative design is a rule-based iterative design process driven by algorithmic models and parameters to automatically generate, iterate, and optimize design possibilities by defining constraints and high-level objectives. Similarly, Autodesk [2] defines generative design as a computational process that leverages computing power to execute a vast number of accurate, real-world simulations to derive a set of optimal design solutions for a predefined problem. Generative design relies on algorithms to achieve optimized outcomes, meaning it adheres to a structured set of instructions governing how input data is processed

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to generate outputs. This technology is increasingly applied to engineer complex and high-performing building structures, effectively pushing the boundaries of design capability.

The most powerful capability of generative design lies in its capacity to automatically explore and iterate through design possibilities, permuting the best solutions for designers and decision-makers [3]. The generative design workflow can be summarized into four fundamental steps [4]:

- **Step 1:** The designer defines the design objectives and requirements, incorporating parameters and constraints such as materials, costs, and other criteria.

- **Step 2:** The designer deploys algorithms to execute the generative process. The design solution yields a diverse set of alternatives capable of fulfilling multiple functional requirements, accompanied by performance analyses to support the subsequent decision-making process.

- **Step 3:** Upon obtaining preliminary results, designers review and evaluate the various alternatives, iteratively adjusting parameters and objectives to refine the problem formulation. This iterative process, driven by the synergy between human intelligence and artificial intelligence, continues until the most suitable solution is identified.

- **Step 4:** The final design undergoes further evaluation by the designer before moving to production, ensuring full compliance with established standards and goals.

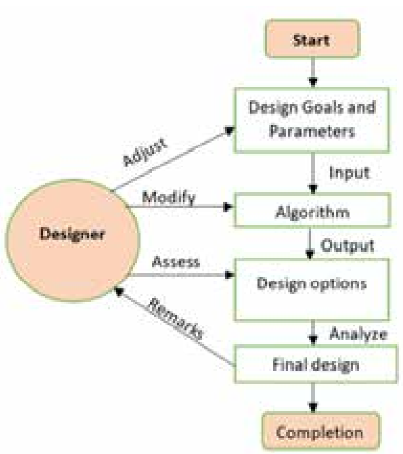

Figure 1: Generative design workflow

2.2. The Role of the Architect in Generative Design Workflows

With the integration of generative design workflows, the role of the architect has transformed significantly. Within the four-step design framework proposed by M. McKnight, it is evident that the architect remains central, though their specific responsibilities vary across each stage. Thus, the architect's role in the context of generative design is not being replaced; rather, it shifts from a direct form-giver to a director and decision-maker. Architects no longer design individual, specific alternatives; instead, they design the system that generates those alternatives and assume responsibility for selecting from the resulting outcomes. This shift elevates the importance of the evaluation and selection process, while placing higher demands on cognition, critical thinking, and the ability to control subjective factors. Consequently, identifying and mitigating cognitive biases during decision-making has become a pivotal issue that directly influences the quality of design outcomes when utilizing generative design.

2.3. Cognitive Biases in Human-Generative Design Interaction

Cognitive biases warrant particular attention in the design process because they represent systematic deviations in human perception, information processing, and decision-making, often leading to suboptimal judgments. These deviations frequently stem from cognitive heuristics—unconscious mental shortcuts or rules of thumb used to process information. These heuristics cause us to interpret data subjectively, heavily influenced by past experience, emotions, preconceptions, or contextual framing [5]. Because cognitive biases are inherent to human nature, individuals are generally unaware of their existence and influence. Consequently, even well-intentioned experts or practitioners remain susceptible to making biased decisions. In fact, research indicates that many types of bias do not correlate with cognitive ability or general intelligence [6]. According to Popescu [7], nine potential biases were identified based on two criteria: cognitive biases capable of directly affecting the creative process within generative design systems, and those that can be readily observed during the ideation phase and are relevant to human-technology interaction in a creative context.

- **Framing Bias**: Occurs when individuals make decisions based on how information is presented rather than on the objective facts themselves.

- **Confirmation Bias:** The tendency to search for, interpret, and favor information that validates preexisting beliefs or hypotheses.

- **Availability Bias:** Refers to situations where easily accessible information is prioritized over more accurate or representative data.

- **Overconfidence:** Occurs when individuals overestimate their skills, knowledge, or judgments beyond objectively justifiable levels.

- **Anchoring:** Occurs when individuals rely too heavily on the first piece of information encountered when making judgments.

- **Sunk Cost Bias:** Occurs when individuals continue to pursue a course of action because of prior investments of time, money, or resources, even when shifting direction would be more rational.

- **Status-quo Bias:** Refers to the tendency to maintain the current state of affairs and resist changes that alter that baseline.

- **Authority Bias:** The disproportionate tendency to trust and be influenced by information endorsed by an authority figure, assuming it to be inherently correct.

- **Prompt Bias:** A specific bias in generative systems where restricted or poorly formulated inputs compromise the accuracy and reliability of the generated output.

- **Priming Bias:** Occurs when prior exposure to a stimulus unconsciously influences an individual's subsequent response to another stimulus.

However, Popescu's assertions specifically address Generative AI rather than Generative Design. Generative AI creates novel content leveraging advanced machine learning paradigms known as deep learning—algorithms modeled after the learning and decision-making mechanisms of the human brain. These models operate by recognizing and encoding patterns and relationships within massive datasets. They then use this information to comprehend natural language user inputs or queries and synthesize corresponding novel outputs [8]. According to a specialized study by Parametric [9], while both Generative AI and Generative Design aim to generate novel alternatives, they differ fundamentally in methodology. Generative AI relies on data-driven deep learning, whereas Generative Design operates through rule-based algorithmic systems, constraints, and optimization. This perspective aligns with the principles of Algorithmic Architecture, which defines generative systems as rule-based, computational frameworks.

Despite these conceptual differences, both Generative AI and Generative Design yield novel alternatives, and cognitive biases remain systematic errors that arise when humans receive, process information, and select from those alternatives. Consequently, many cognitive biases identified in Generative AI workflows can manifest within Generative Design, particularly those related to confirmation, framing, sunk costs, or the status quo. However, prompt bias is not entirely applicable to Generative Design, as the latter operates primarily via parameters, constraints, and algorithmic models rather than natural language inputs typical of Generative AI.

3. RESEARCH METHODOLOGY

This study employs a literature analysis and synthesis method to systemize the core concepts surrounding generative design, the evolving role of the architect, and cognitive biases within decision-making processes. Concurrently, an empirical survey was conducted with a sample size of $n = 76$ participants, comprising practicing architects and architectural students, to document choice behaviors within various generative design simulation scenarios. The survey data underwent qualitative analysis and was cross-referenced with cognitive bias taxonomies established in prior literature. On this basis, the study evaluates the specific impacts of cognitive biases on human decision-making within generative design environments.

4. RESULTS AND DISCUSSION

4.1. Empirical Results on Architects' Decision-Making Trends

In the fields of architectural design and construction, as the volume of design alternatives generated by generative design increases substantially, the architect's decision-making process grows increasingly complex. Instead of choosing among a small number of alternatives developed by themselves, architects must evaluate and select from a vast population of system-generated variants. Although Generative Design is widely regarded as a tool that supports data-driven and algorithmic decision-making, the final selection process ultimately relies on human judgment. This introduces a paradox: as the number of alternatives expands, the final decision becomes increasingly susceptible to the influence of cognitive biases.

The empirical phase of this study was conducted with a sample size of n = 76 participants, comprising practicing architects and architectural students. To identify these psychological trends concretely, the survey presented a real-world scenario: "Suppose you have spent 3 hours setting up a design algorithm, but the resulting output is not as expected. What would you do?"

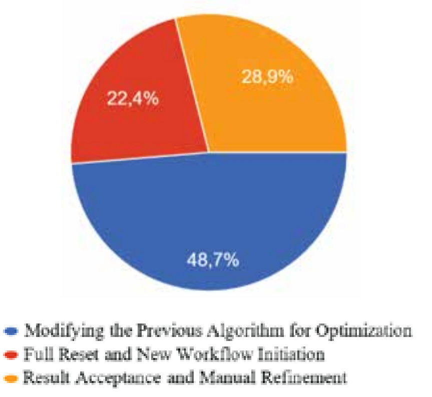

Figure 2: Response rates for the hypothetical scenario regarding algorithmic constraints (n = 76) (Source: Authors' survey, 2026)

The survey results illustrated in Figure 2 reveal that the sunk-cost fallacy and status-quo bias manifested in 48.7% of the responses, where participants chose to continue modifying the existing algorithm for optimization after spending 3 hours constructing the system. This indicates that designers exhibit a tendency to reinvest in an existing system simply because of the substantial time and effort previously expended, even when the current outcomes are inefficient. The more complex the system, the more difficult it is to abandon. Confirmation bias was also evident, as designers operated under the assumption that the initial algorithm was fundamentally correct and merely required further refinement. They attempted to validate their initial hypothesis regarding the algorithmic system rather than restructuring the entire generative logic.

Meanwhile, the 28.9% cohort who chose to accept the current results and perform manual edits exhibited signs of framing bias. When the algorithmic output is framed as a reference benchmark rather than an absolute solution, it drives designers to perform localized adjustments rather than recalibrating the entire parametric chain. Concurrently, the compounding effects of the sunk-cost fallacy and status-quo bias further reinforced the decision to maintain the existing output. Consequently, up to 77.6% of the participants exhibited cognitive biases encompassing sunk costs, status quo, and framing effects. These findings demonstrate that within generative design workflows, designers do not act entirely "rationally" in accordance with algorithmic logic.

To further verify other psychological dimensions, the subsequent survey question aimed to determine the presence of overconfidence bias and confirmation bias. Participants were requested to evaluate the alternatives presented in Figure 3 and select the option they perceived to be generated by a more complex algorithm.

Figure 3: Surface morphology options A, B, and C utilized in the second survey question (Source: Synthesized by the authors, 2026)

The results illustrated in Figure 4 register an overwhelming majority, with 68.4% of participants selecting option C. In reality, option A represents the alternative engineered by a more complex algorithmic system, which utilizes the Fibonacci sequence for surface subdivision, whereas the remaining two options merely rely on a simple, linear U,V grid subdivision. This discrepancy arises because decision-makers exhibit a tendency to heuristically assume that highly detailed alternatives are inherently more computationally complex than less detailed ones. This aligns with confirmation bias, where individuals selectively process information to validate preexisting beliefs, thereby leading to erroneous decisions. Furthermore, deliberately rendering the background of option C in a prominent red color succeeded in capturing the participants' visual attention and distorting their perception - a classic manifestation of the framing effect. This demonstrates that participants frequently make choices based on the manner in which information is presented rather than its objective substance.

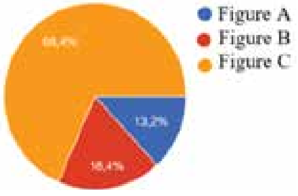

Figure 4: Participants' visual assessment rates regarding the algorithmic complexity of design alternatives (n = 76) (Source: Authors' survey, 2026)

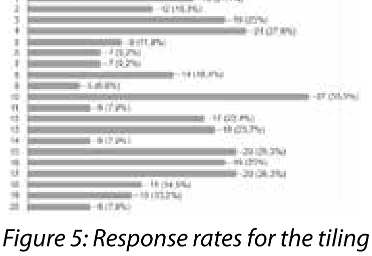

Figure 5: Response rates for the tiling design selection within a large-scale generative solution space (n = 76) (Source: Authors' survey, 2026)

The next section of the survey presented a scenario involving the selection of a tiling design out of 20 alternatives generated via generative design. Although all options were of equivalent quality, the results illustrated in Figure 5, participants overwhelmingly selected Option 10, which featured a red background, capturing an absolute majority of 35.5% and topping the selection list. This clearly illustrates the framing effect, where an alternative is selected primarily because it is presented more prominently than others. Additionally, the priming effect must also be addressed in this context; having encountered a similar visual stimulus in the previous question, participants were unconsciously conditioned to favor the red-background option when comparing algorithmic complexity among the three prior cases.

4.2. Discussion

This study demonstrates that generative design does not diminish the role of the architect but rather shifts the focus from direct form-giving to system design and decision-making. As the volume of alternatives multiplies, the selection process becomes increasingly complex and susceptible to cognitive biases such as confirmation bias, the sunk-cost fallacy, status-quo bias, and the framing effect. The empirical survey results indicate that participants are frequently influenced by the presentation of information rather than its objective quality, driving them to prioritize familiar solutions or rely on "cognitive heuristics" instead of executing an objective evaluation rooted in algorithmic logic.

Therefore, alongside algorithmic development, significant emphasis must be placed on de-biasing methodologies through transparent evaluation criteria, critical thinking, and structured decision-making frameworks to enhance practical application efficiency. Concurrently, architectural education in the digital era must strike a balance between advancing technical skills and raising awareness of the cognitive and psychological factors that govern the design process.

5. CONCLUSION

Generative design is fundamentally transforming architectural workflows by enabling the simultaneous generation and optimization of multiple design alternatives based on algorithms and parametric data. However, this study reveals that decision-making within these digital environments remains heavily influenced by human cognitive biases. Biases such as confirmation, sunk cost, status quo, and framing directly manipulate how architects evaluate and select design variations.

The empirical survey findings demonstrate that designers do not act entirely in accordance with the rational logic of algorithmic systems; instead, their judgments remain bound to past experiences, cognitive habits, and the framing of information. This underscores that the implementation of generative design is not merely a technological challenge, but a cognitive and behavioral issue inherent to the design workflow. Consequently, identifying and mitigating cognitive biases is imperative to enhance objectivity and efficiency within contemporary computational architecture decision-making.

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