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Article

Cognitive processes in parametric design: A systematic literature review of methods, models, and future directions

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ABSTRACT

This study explores cognitive processes in parametric design environments (PDEs), synthesizing current research to identify key methodologies, theoretical models, and factors that influence design cognition. The review addresses challenges like cognitive overload, algorithmic dependence, and the learning gap between novice and expert designers. A systematic literature review (SLR), following PRISMA guidelines for transparency and reproducibility, was conducted to analyze studies on design cognition in PDEs, with a focus on empirical research examining cognitive processes, design behavior, and educational strategies. The review reveals that PDEs encourage creativity, iterative problem-solving, and dynamic design exploration but also pose cognitive challenges, particularly for inexperienced designers. Expert designers exhibit greater algorithmic fluency and adaptability, while novices often experience cognitive strain and reliance on black-box thinking, which limits their creative engagement. Educational gaps persist, highlighting the need for scaffolded learning models, hands-on workshops, and non-digital exercises to build algorithmic skills progressively. Additionally, the lack of standardized frameworks for evaluating algorithm quality and cognitive performance underscores the need for further research. This review provides insights for educators and researchers to bridge the gap between technical proficiency and creative innovation in parametric design.

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INTRODUCTION

Design is an essential cognitive process, shaped by various internal and external factors. Several cognitive studies focus on the design process (Cross, 2001), with the origins of research in design cognition often attributed to Eastman's (1969) foundational work. Dinar et al. (2015) defined design cognition as the analysis of the information designers use during the design process. Dinar et al. (2015) reviewed empirical studies on design cognition and revealed that most existing studies focus on the early, somewhat unclear stages of the design process, known as conceptual design. Despite the significant number of empirical studies, many researchers emphasize that the nature of the cognitive

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processes involved in design remains unclear (Dorst & Cross, 2001; Jin & Benami, 2010; Kim & Ryu, 2014).

While design cognition has been studied extensively in general design contexts, the focus on cognitive processes within parametric design environments (PDE) has been relatively limited. Design cognition studies examine the influence of various factors such as design environments (Trump & Shealy, 2023), restorative experience (Ignacio & Shealy, 2023), situatedness (Gero & Milovanovic, 2023), and empathy (Aktaş Yanaş & Gül, 2025) on design processes. However, there are very few studies on parametric design cognition. Despite the growing popularity of parametric design in architecture, empirical evidence on designers' behaviors in PDE is limited (Yu & Gero, 2016). While much of the literature focuses on technological advancements in parametric design tools, our understanding of the cognitive processes underlying PDEs remains limited (Oxman & Gu, 2015).

Systematic literature reviews (SLR) can be beneficial in filling these knowledge gaps because they are commonly used to synthesize evidence and reduce bias. SLR systematically collects, synthesizes, and analyzes all relevant publications on a given topic using predetermined inclusion criteria, and it is held to the same standard as empirical research due to its transparency and repeatability. Conducting an SLR on cognitive processes in PDE can provide valuable insights into how designers think and study within these environments, highlighting common findings and differing perspectives. According to Marzano and Kendall (2006), cognitive tasks involve at least one of the following categories: decision-making, problem-solving, experimenting, and investigating. In the context of parametric design, all these categories are intensely utilized as integral components of the cognitive system in the design process.

Given the complexity and importance of these cognitive processes, it is crucial to synthesize existing research to better understand how they manifest in PDEs. While there are several SLRs in related areas of design cognition, such as Dinar et al. (2015) on empirical studies of design cognition, Jiang and Yen (2009) on protocol analysis, and Hay et al. (2017) on cognition in conceptual design, none of these studies specifically focus on the cognitive dimensions of PDEs. This gap highlights the need for a comprehensive SLR to synthesize existing research and provide a clearer understanding of cognitive processes unique to PDE.

This study aims to systematically review studies that focus on design cognition in PDE and seeks to answer the following questions: (i) What is our current understanding of cognitive processes in PDE? (ii) What methods are applied in this field? (iii) What variables are typically examined in experimental studies? By addressing these questions, the study aims to bridge the knowledge gap in this area and offer a comprehensive synthesis of existing research on parametric design cognition. Unlike previous reviews that broadly address design cognition, this study focuses explicitly on the unique cognitive processes that differentiate PDE from traditional design environments. Furthermore, this review focuses on empirical studies within PDE, examining their methods and procedures to inform future research. It will also discuss the limitations of these methods and models, providing a deeper exploration of the impact of PDE on novice designers. Additionally, the review will address the challenges faced by educators, especially in countries with limited educational resources, and propose solutions to bridge these gaps.

Design Cognition and Parametric Design

Design is recognized as a complex cognitive activity, requiring designers to analyze, interpret, and solve problems through an array of structured and unstructured processes (Goldschmidt, 1991). Cognitive design studies often examine how designers engage in divergent and convergent thinking, with divergent thinking fostering the generation of multiple creative ideas and convergent thinking guiding the selection of the most feasible solution (Cross, 2001). This interplay between exploration and refinement is critical in design problem-solving, particularly in environments where dynamic changes and iterations are essential. Research on design cognition highlights the role of mental strategies such as abstraction, problem decomposition, and reflective thinking, all which support decision-making during the design process (Goldschmidt, 1991; Oxman, 2001). Protocol analysis is a widely used method to study these cognitive activities (Blandino et al., 2023), enabling the observation of designers' thought processes in real time. This method has evolved over the years, with recent studies incorporating multimodal protocols that use dual verbal protocols (Leem & Lee, 2024), eye-tracking (Härkki, 2023), video recordings (Gürel & Şenyapılı Ozcan, 2023), and even biometric analysis (Yu et al., 2023). These multimodal approaches offer a more comprehensive understanding of cognitive load, mental strategies, and problem-solving in design environments. These analyses reveal that designers engage in iterative processes, revisiting earlier design decisions as new information emerges (Oxman, 2001). Such insights could also provide a foundation for understanding cognitive processes in PDE, which differ significantly from traditional design settings.

PDEs introduce unique cognitive demands that challenge the traditional approaches used in design cognition (Oxman & Gu, 2015). Unlike traditional design, which often follows a linear process, PDEs require designers to engage with non-linear, iterative exploration through parametric logic. In PDEs, relationships between parameters must be defined before generating design outputs, necessitating a higher level of abstraction and systematic thinking (Lee & Ostwald, 2019). Recent research emphasizes that this shift from manual design to parameter-driven logic requires cognitive adaptation, particularly for novice designers who are unfamiliar with computational logic (Dissaux & Jancart, 2022; Liang et al., 2019).

Understanding how changes in one parameter impact the entire design system is a significant cognitive challenge in PDEs. Unlike traditional design, where design elements are modified directly, PDEs require designers to define interdependent relationships between design elements. This relational thinking necessitates the use of computational frameworks that support parametric logic. Tools like Grasshopper and Dynamo enable designers to visualize these relationships through a node-based interface, where inputs, transformations, and outputs are visually represented as components in a flowchart (Caetano et al., 2020). These tools reduce the need for textual coding, but they introduce new tasks as abstraction, rule-based thinking, and spatial reasoning which can cause cognitive load.

Cognitive load is another significant factor in PDEs. The dual requirement to manage parameter logic while also focusing on design goals increases the cognitive load on designers (Lee & Ostwald, 2019). Novice designers, in particular, are susceptible to cognitive overload due to unfamiliarity with parametric workflows and the complexity of parameter-based relationships (Dissaux & Jancart, 2022). To address this, design educators have focused on developing step-by-step pedagogical approaches that gradually introduce students to parametric thinking. Visual programming tools play a key role in this process, as they allow designers to manipulate visual representations of parameters, thereby reducing the cognitive load associated with text-based coding (Caetano et al., 2020; Woodbury, 2010).

One of the most critical cognitive shifts in PDEs is the move from product-based thinking to process-based thinking (Lee et al., 2013). In traditional design, the designer focuses on achieving a final product, often working in a linear sequence. In contrast, PDEs emphasize the creation of a generative system that produces multiple design outputs. This shift changes how designers approach problem-solving, as they must think about processes, rules, and relationships rather than static objects (Caetano et al., 2020). This process-oriented thinking requires designers to conceptualize and manage the relationships between interdependent components, reflecting a higher level of cognitive complexity.

Another prominent issue in PDEs is the tendency toward "black-box thinking." When designers rely on pre-built algorithms or imported parametric scripts, they may lose sight of the logic and structure underlying the design process (Woodbury, 2010). This reliance on pre-built solutions can hinder creativity and limit the designer's ability to adapt to new design challenges. Vazquez (2024) suggest that educators should encourage students to build their own parametric rules and algorithms rather than relying on external libraries. By promoting computational literacy, designers can maintain greater control over the process, develop critical thinking skills, and avoid dependency on "black-box" systems.

Parametric design is used in various fields such as facade design (Dervishaj & Gudmundsson, 2024), structural optimization (Zhang et al., 2024), and urban planning (Tehrani et al., 2024). However, research on PDE education remains limited, primarily due to the high cognitive load for novices and black-box thinking. To address these challenges, it is essential to investigate the cognitive mechanisms of both novice and expert designers in PDEs. Therefore, this study systematically reviews existing research, examines methodologies and variables, and discusses the strengths and weaknesses of current approaches.

RESEARCH METHOD

This section outlines the systematic methodology used to examine cognitive processes specifically within PDEs. The review follows the PRISMA guidelines, focusing on cognitive processes in parametric design, rather than general design. The subsections of this section include research design (3.1), which outlines the overall approach, the databases used for literature gathering (3.2), the inclusion and exclusion criteria for selecting relevant studies (3.3), the search strategy applied to ensure a broad and relevant collection of literature (3.4), and the selection process for narrowing down the studies (3.5). By focusing on parametric design, this section ensures that the cognitive processes analyzed are specific to the unique characteristics of PDEs, rather than general design environments.

Research Design

This SLR was conducted in line with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Moher et al., 2009). The purpose of this review is to thoroughly analyze studies examining cognitive processes in PDEs.

Databases

The studies included in this review were gathered from the SCOPUS and Web of Science (WoS) digital databases. To broaden the scope of the research, other databases such as IEEE Xplore, ACM Digital Library, ScienceDirect, JSTOR, EBSCO, and Taylor & Francis were also considered. However, SCOPUS and WoS were chosen as the primary databases because they provide comprehensive scientific research, including journal articles and conference papers (Zhu & Liu, 2020).

Inclusion Criteria

To be included in this SLR, studies had to meet the following criteria:

- The study must provide a theoretical or applied review of cognitive processes in PDEs.
- The study must present a model, technique, or method to evaluate one or more factors influencing cognitive thinking in PDE.
- The cognitive processes analyzed must involve a design problem.

The following exclusion criteria were also applied:

- The study is not in English,
- The study is not related to parametric design processes,
- The profiles of the participants or trainees involved in the study are not clearly defined,
- The studies are duplicate or repetitive across different databases,
- The full text of the article or paper is not accessible.

Search Strategy

The search strategy aimed to identify primary studies relevant to this literature review. Keywords were selected to cover two main concepts: parametric design and cognitive processes or education/training. To ensure that as many relevant research studies as possible were included, the search terms were derived from previous searches and are presented in Table 1.

Selection Process

The database search was conducted on December 1, 2024, and a total of 1,436 records were obtained (801 from SCOPUS, 863 from WoS). After removing duplicate entries, the selection process began with 874 records. This process consisted of two stages. In the first stage, the titles and abstracts of each study that met the inclusion and exclusion criteria were analyzed. In the second stage, the list was narrowed down to 30 studies (Figure 1).

Subsequently, the second review of the selection process, in which the full texts were analyzed, was conducted. As a result of this second review, 18 studies were deemed appropriate for inclusion, comprising 5 conference papers and 13 journal articles. To ensure the selection process was as inclusive as possible, no year restrictions were applied as a selection criterion. The distribution of the selected publications by year is shown in Figure 2. It can be observed that the selected studies span the years 2012 to 2024, with the highest number of studies conducted in 2012.

The selected studies were coded and analyzed using MaxQda and Microsoft Excel. The tables presented in the report were generated using MaxQda's code relation browser for the analysis. The themes or categories that emerged during the coding process were discussed in the findings section.

FINDINGS

As a result of the SLR, a bibliometric analysis was first conducted to identify the leading journals and conferences in the field. Subsequently, the reviewed studies were classified based on the data collection methods they employed, and the most common protocol analysis methods were examined. Since the studies identified through the SLR are experimental, the experimental conditions vary. In the following sections, these variables are analyzed under three headings: participant groups, design tasks, and control group variables.

Bibliometric Analysis

The SLR included a bibliometric analysis of studies on cognitive processes in parametric design. The review revealed that studies in this area began to increase in 2012, with early publications being preliminary experimental studies presented at conferences. Over time, the results of these studies were published in journals.

The most frequently published journals in this field are the International Journal of Architectural Computing and the International Journal of Design Creativity and Innovation. Ju Hyun Lee (Lee et al., 2013; Lee et al., 2015, Lee et al., 2016; Lee & Ostwald, 2019; Lee & Ostwald, 2020) and Rongrong Yu (Yu et al., 2012b; Yu et al., 2012a; Yu et al., 2013; Yu et al., 2018; Yu & Gero, 2016) are the two researchers with the most publications in this field.

Table 1. Keywords of the study focus

Database	Results	Keyword search and other applied filters
SCOPUS	801	TITLE-ABS-KEY (“parametric design” OR “parametric design environment”) AND TITLE-ABS-KEY (cognit* OR "protocol analysis" OR "design thinking" OR "design education" OR educat* OR evaluation) AND (LIMIT-TO (LANGUAGE, "English")
WoS	863	Results for “parametric design” OR “parametric design environment” (Topic) AND cognit* OR "protocol analysis" OR "design thinking" OR "design education" OR educat* OR evaluation (Topic) AND English (Languages) and Article or Proceeding Paper (Document Types) and English (Languages)

The * symbol has been used as a truncation operator to search for documents containing the root of the term followed by any number of characters.

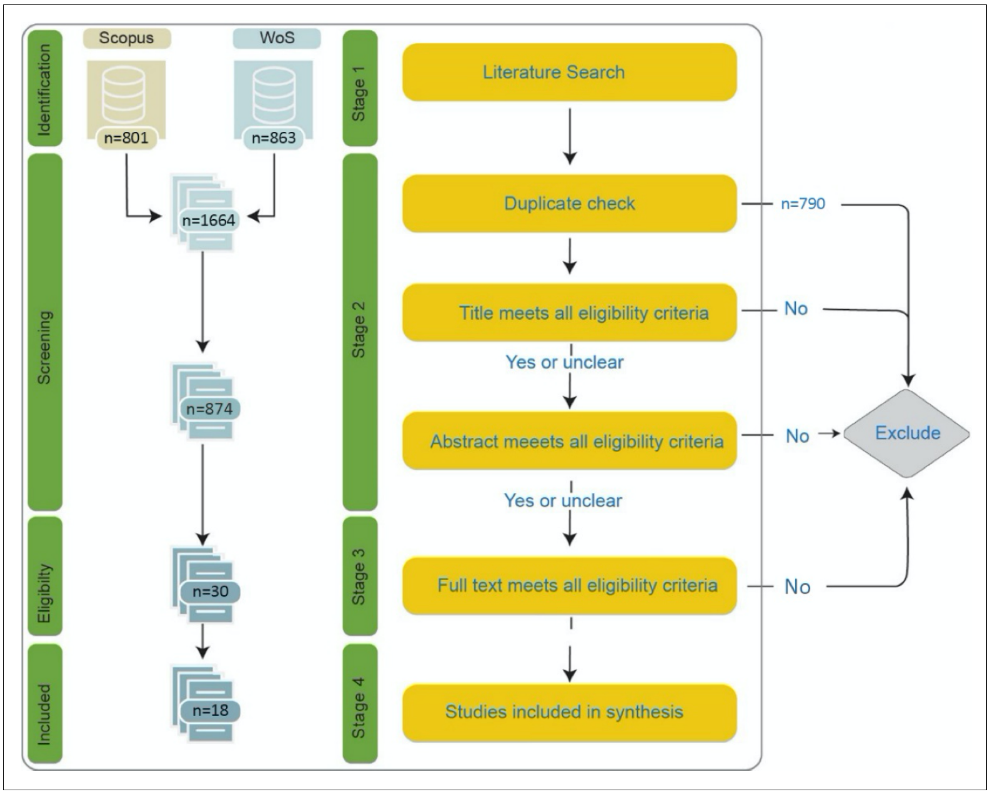

Figure 1. Study Flow Chart.

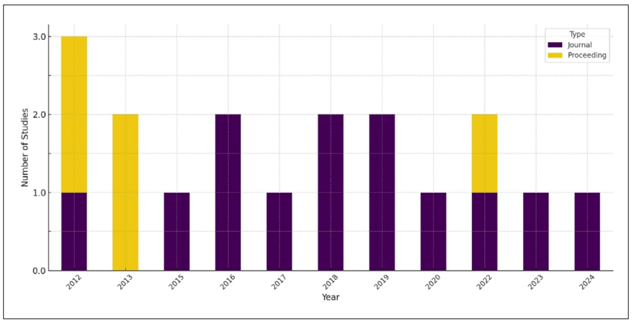

Figure 2. Distribution of the selected publications by year.

Table 2. Data collection methods used in the field of parametric design cognition

Methods	Studies
Survey	(Alalouch, 2018; Namoun et al., 2019; Yang et al., 2022)
Interview	(Dissaux & Jancart, 2022; Lee & Ostwald, 2020; Namoun et al., 2019)
Personal Experience	(Aish & Hanna, 2017)
Protocol Analysis	Listed in Table 3

Data Collection Methods

In studies on cognitive processes in PDE, various data collection methods are used to analyze users' design processes. These methods include surveys, interviews, personal experience, and protocol analysis. Table 2 presents the distribution of data collection methods used in studies on parametric design cognition.

In cognitive process studies, surveys are used to allow participants to describe their own cognitive processes through pre-structured questions. In Alalouch's (2018) study, participants' cognitive processes were assessed using questions designed with a five-point likert scale. The survey employed in that study measured three factors: cognitive strategies, intellectual abilities, and attitudes of the participants. However, this method relies on self-assessment, which can lead to reliability issues. To address this problem, Namoun et al. (2019) combined the survey method with the think-aloud protocol used in protocol analysis.

The use of surveys in cognitive process studies requires self-evaluation, meaning the reliability of the data is contingent on the objectivity of the participants. Nevertheless, participants tend to evaluate the design environments or tools they use more objectively than their own cognitive processes. For this reason, the survey method can be used to measure usability, as in Namoun et al. (2019)'s, study, or to collect preliminary data, as in Yang et al. (2022)'s, study.

In the interview method, semi-structured questions are used to gather information about the participants' design processes, followed by quantitative evaluations. Like surveys, interviews face reliability challenges, and as such, they should be validated through cross-referencing with other data, as demonstrated by Dissaux & Jancart, (2022); Lee & Ostwald, (2020).

Aish & Hanna (2017) took a different approach, analyzing parametric design processes based on their own experiences. In their study, the authors evaluated the three most commonly used environments in PDE by discussing the challenges they encountered. However, this method is considered more of a preliminary trial and requires validation through comparisons with the experiences of other users.

The most frequently used method in this field is protocol analysis. In this approach, participants are asked to think aloud during the design process, and their processes are recorded. The recording can be audio, or video as was the case in some studies. In PDE research, screen recordings are also commonly used. The consistency of the analysis improves as the volume of collected data increases. The reliability of the analysis process must also be tested. In studies where the analysis is performed by a single researcher, the process is repeated at two different times and the results are compared. In studies involving multiple researchers, the consistency between their analyses is compared statistically. Additionally, since protocol analysis examines the design process, it is often supplemented by surveys or interviews with participants at the end of the process.

Protocol Models

Several theoretical models are used to analyze the data collected during protocol analyses. These models divide design processes into steps that are coded according to the selected model, then analyzed in terms of step sequences, repetitions, and durations. Table 3 shows the coding models used in the studies identified through the SLR, with FBS (Function-Behavior-Structure) and PPC (Physical-Perceptual-Conceptual) models being the most frequently used.

Table 3. Analysis models used in protocol analyses

Models	Studies
Language-oriented coding	(Lee et al., 2016)
PSFIE	(Chien & Yeh, 2012)
PPC	(Lee et al., 2013, 2015, 2016; Lee & Ostwald, 2019; Öztürk Kösenciğ & Özbayraktar, 2024)
DMP	(Lee & Ostwald, 2020)
Knowledge retrieval	(Dissaux & Jancart, 2022)
FBS	(Gürel & Şenyapılı Ozcan, 2023; Yu et al., 2012b, 2013, 2018; Yu & Gero, 2016)

The FBS (Function-Behavior-Structure) model developed by Gero, (1990) is one of the most widely used models in protocol studies on design. This model has been preferred in PDE studies due to its potential to cover the most meaningful cognitive aspects of the design process Yu et al., (2018). The FBS model's formulation is presented in Figure 3.

The FBS model defines the design process through six variables and eight transitions between them. These variables are:

- Requirements (R): This variable describes the things necessary to solve the design problem, independent of the designer.
- Function (F): It defines the purpose of the design and the designed object.
- Behavior (B): This includes the expected behavior (Be) and the behavior resulting from the structure (Bs) of the design object.
- Structure (S): This represents the components that make up the design object and the relationships between them.
- Document (D): It defines the representational outputs needed to communicate the design.

The transitions between these steps, as seen in Figure 3, include formulation, synthesis, analysis, evaluation, documentation, and reformulation I, II, and III.

The FBS model can be used directly, as in the studies by Yu et al., (2018); Yu and Gero, (2016), or it can be separated into subcategories of design and algorithms, as seen in Yu et al. (2013)'s study. Furthermore, in a study by Yu et al. (2012b), an extended version of the decomposed FBS model incorporates the concepts of external, interpretive, and expected worlds.

Another commonly used model is Suwa et al., (1998)'s. PPFC (Physical-Perceptual-Functional-Conceptual) model, adapted for PDE. The adapted version of the PPC model, shown in Table 4, consists of physical, perceptual, and conceptual variables.

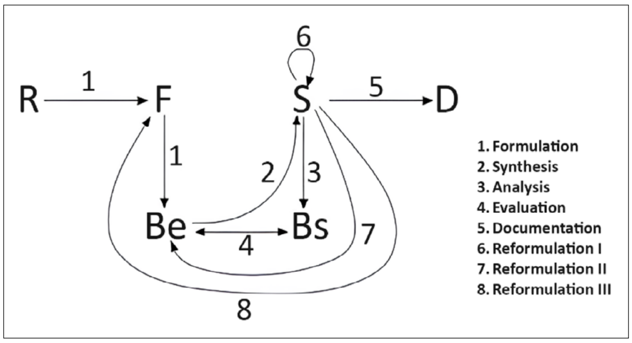

Figure 3. FBS model.

Table 4. PPC model (Lee et al. 2013)

Level	Category	Subclasses	Description
Physical	Geometry	G-Geometry	Create geometries without an algorithm
		G-Change	Change existing geometries
	Algorithm	A-Parameter	Create initial parameters
		A-Change Parameter	Change existing parameters
		A-Rule	Create initial rules
		A-Change Rule	Change existing rules
		A-Reference	Retrieve or get references
Perceptual	Geometry	P-Geometry	Attend to existing geometries
	Algorithm	P-Algorithm	Attend to existing algorithms
Conceptual	Problem-finding	F-Initial Goal	Introduce new ideas or goals based on given design brief
		F-Geometry Sub Goal	Introduce new geometric ideas extended from a previous idea
		F-Algorithm Sub Goal	Introduce new algorithmic ideas extended from a previous idea
	Solution-generating	G-Generation	Make generation or variation
	Solution-evaluating	E-Geometry	Evaluate primitives or existing geometries
		E-Parameter	Evaluate existing parameters
		E-Rule	Evaluate existing rules
		E-Reference	Evaluate existing references

The physical variable defines production actions and is divided into geometric and algorithmic categories. Modeling functions fall under the geometric category, while parametric rule sequences are classified under the algorithmic category. The perceptual variable refers to the mental visualization and consideration of the produced objects, and it is also divided into geometric and algorithmic categories. The conceptual variable, adapted from the study of Gero & Mc Neill (1998), consists of three classes: problem identification, solution generation, and evaluation. Like the FBS model, the PPC model can be used independently or in combination with other models. For example, in study by Lee et al., (2016), the PPC model was used in conjunction with a newly developed semantic model to investigate the relationship between cognitive processes and language.

Table 5. Data evaluation methods used

Methods	Studies
Statistics and Descriptive	(Alalouch, 2018; Chien & Yeh, 2012; Gürel & Şenyapılı Ozcan, 2023; Lee et al., 2013, 2015, 2016; Lee & Ostwald, 2019, 2020; Namoun et al., 2019; Yang et al., 2022; Yu et al., 2013, 2018; Yu & Gero, 2016)
CAT (Creativty Assessment)	(Lee et al., 2013, 2015; Yang et al., 2022; Yu et al., 2018)
Learning Curve	(Aish & Hanna, 2017)
Linkography	(Lee et al., 2016; Lee & Ostwald, 2019; Öztürk Kösenciĝ & Özbayraktar, 2024)

Data Evaluation Methods

The data analysis methods used in the identified studies are listed in Table 5. The first method is statistical analysis, used in studies such as Chien & Yeh's (2012) work for evaluating the design processes decoded through protocol analysis using standard deviation and percentage distribution. More advanced methods like the U-test and regression are used in studies (Alalouch, 2018; Yang et al., 2022) with control groups.

Descriptive analysis methods are primarily used to examine correlations, while the Linkography method is used to analyze transitions between codes. Linkography was employed by Lee & Ostwald (2019) to analyze entropy between codes, allowing the visualization of relationships between steps in the design process, as shown in Figure 4.

The learning curve method was used by Aish & Hanna (2017). In their study, problems encountered in the design environment were considered learning thresholds, and personal experiences were graphically represented and compared based on the issues faced during the process. MacLean et al. (1990) defined learning as the overcoming

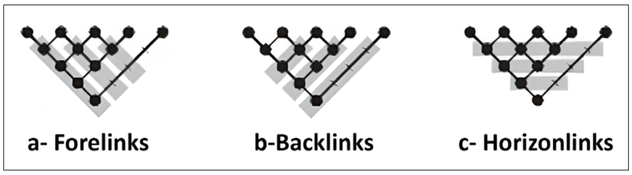

Figure 4. Linkography analysis samples (Lee & Ostwald, 2019).

of encountered problems. Myers (2002) suggested that effective learning can be represented by a smooth-sloped curve. Based on this, Aish & Hanna, (2017) concluded that Grasshopper is more conducive to learning in PDE.

The CAT (Creativity Assessment Tool) method is used in this field to evaluate design outcomes. These are rubric scales designed to measure creativity, allowing the relationships between processes and the final product to be examined. The rubric CAT scales used in studies identified through the SLR are based on the scale developed by Amabile, (1983). While these scales serve a similar function, there are slight variations between them. For example, the scales used in Lee et al. (2013); Lee et al. (2015) assess originality, usefulness, complexity, and aesthetics, whereas Yu et al. (2018) replaced complexity and aesthetics with the criterion of surprise. Yang et al. (2022), originality, usefulness, quality, and manufacturability were used as criteria. Upon reviewing the criteria used in CAT scales, originality and usefulness are consistently repeated. These scales can be used by the authors themselves or, as in Lee et al. (2013) study, to gather expert opinions.

Participant Groups

The distribution of participant groups in the studies included in this systematic review is presented in Table 6. Undergraduate students are defined as "students," while professionals with bachelor's degrees are categorized as "professional groups." A minimum of two years of experience with PDE is used to distinguish between experienced and inexperienced participants.

The most frequently studied group in PDE research consists of experienced architects, as PDE requires more prior knowledge than traditional design environments. Studies by Yu et al. (2018); Yu & Gero, (2016) analyzed the cognitive processes of experienced architects. However, there is limited research focusing on inexperienced users in PDE. Dissaux & Jancart, (2022) analyzed the thinking processes of inexperienced users during learning activities.

The second most common participant group consists of architects with mixed experience levels. In these studies, participants are separated based on their experience in PDE. Studies by Chien & Yeh (2012); Lee et al., (2015) analyzed the cognitive processes of architects with mixed experience levels. In fields outside of architecture, the web design process was examined with twenty-four software developers by Namoun et al. (2019), while the creative thinking process was analyzed with 110 participants by Yang et al. (2022).

Table 6. Participant groups according to the SLR

Groups	Studies
Experienced professionals	(Gürel & Şenyapılı Ozcan, 2023; Lee et al., 2013, 2016; Lee & Ostwald, 2019, 2020; Öztürk Kösenciĝ & Özbayraktar, 2024; Yu et al., 2012b, 2018; Yu & Gero, 2016)
Inexperienced professionals	(Yu et al., 2012a)
Mixed professionals	(Chien & Yeh, 2012; Lee et al., 2015; Yu et al., 2013)
Mixed designers	(Namoun et al., 2019; Yang et al., 2022)
Students	(Alalouch, 2018; Dissaux & Jancart, 2022)

Design Tasks

The design tasks given to participants in the studies are listed in Table 7. The most frequently used design task is high-rise building design, consistent with the focus on form exploration in PDE. In these studies, the emphasis is on the building envelope rather than interior configurations. For example, Chien & Yeh (2012); Lee et al., (2013) focused on high-rise building design. Other tasks used in the studies include pavilion, bridge, and public education center design.

While parametric design is commonly used in engineering, this review focused on architecture-related studies. However, a few examples from software engineering and industrial design were considered. For instance, Namoun et al. (2019) explored website design, while examined earphone design.

Experimental Variables

In the reviewed studies, it was observed that participant groups were generally small, as is typical for protocol analysis. In studies (Dissaux & Jancart 2022; Lee et al. 2016; Yu et al. 2012a) where the participant group consisted of only two or three individuals, no variables were employed, and the cognitive processes of the designers were examined directly.

Table 7. Design tasks according to the SLR

Design Task	Studies
Website	(Namoun et al., 2019)
Curve Control	(Aish & Hanna, 2017)
High-rise building	(Chien & Yeh, 2012; Dissaux & Jancart, 2022; Lee et al., 2013, 2016; Lee & Ostwald, 2019, 2020; Yu et al., 2012b)
Pavillion	(Chien & Yeh, 2012; Dissaux & Jancart, 2022; Öztürk Kösenciĝ & Özbayraktar, 2024)
Pedestrian bridge	(Dissaux & Jancart, 2022)
Shopping mall	(Yu et al., 2013, 2018; Yu & Gero, 2016)
Community center	(Yu et al., 2013, 2018; Yu & Gero, 2016)
Vehicle stop	(Alalouch, 2018; Chien & Yeh, 2012)
Shelter	(Gürel & Şenyapılı Ozcan, 2023)

Table 8. Variables examined in studies

Variables	Studies
None	(Dissaux & Jancart, 2022; Lee et al., 2016; Yang et al., 2022; Yu et al., 2012a)
Environment	(Aish & Hanna, 2017; Chien & Yeh, 2012; Gürel & Şenyapılı Ozcan, 2023; Lee et al., 2013, 2015; Lee & Ostwald, 2019, 2020; Namoun et al., 2019; Öztürk Kösenciğ & Özbayraktar, 2024; Yu et al., 2013, 2018; Yu & Gero, 2016)
Experience	(Alalouch, 2018; Chien & Yeh, 2012; Lee et al., 2013, 2015; Lee & Ostwald, 2019, 2020; Namoun et al., 2019)

In studies where cognitive processes are compared based on variables, two primary variables are identified: environment and experience (Table 8). In research examining the experience variable, participants are classified according to their experience in PDE. Alalouch (2018) categorized users based on their experience with different modeling software. Similarly, Lee et al., (2013); Lee & Ostwald, (2019) and Namoun et al. (2019) divided users into two groups: Experts and novices. This allowed for a comparison of the cognitive processes of participants working in the same environment on the same design problem, investigating the impact of experience on cognitive processes.

In studies where the environment is the variable, design processes are compared using different software and tools as design environments. Aish & Hanna, (2017) performed the same design task using different software, while Yu et al. (2018); Yu & Gero (2016) compared design processes conducted in geometric modeling environments (GME) and PDE by using different design problems. Chien & Yeh, (2012) compared design processes across three environments: PDE, GME, and traditional pen-and-paper design. In Lee & Ostwald's, (2020), study involving six participants, participants were divided into experts and novices based on their experience. Additionally, one participant from each group worked in a code-based environment, while the others used a visual programming environment. This allowed for an investigation of the effects of both experience and environment on cognitive processes during design. The same method was also employed by Lee et al., (2015).

DISCUSSION

The studies summarized in Table 9 highlight key factors influencing cognitive processes in PDEs, with a focus on experience and environment. Protocol analysis, used extensively across the reviewed studies, reveals how designers interact with parametric tools and adapt their cognitive strategies during design tasks. Frameworks such as FBS (Öztürk Kösenciğ & Özbayraktar, 2024; Yu et al., 2012a; Yu et al., 2012b) and PPC (Gürel & Şenyapılı Ozcan, 2023; Lee et al., 2013; Lee & Ostwald, 2019) are central to evaluating design behavior.

Experience consistently emerges as a significant variable, with expert designers demonstrating greater fluency and creativity, while novices frequently need on external assistance, such as tutorial videos or assistants, to navigate PDEs (Dissaux & Jancart, 2022; Namoun et al., 2019). Comparisons between PDEs and GMEs suggest that parametric tools can foster more design exploration, but may also lead to increased cognitive load, particularly for less experienced users (Gürel & Şenyapılı Ozcan, 2023; Yu et al., 2013; Yu & Gero, 2016). Lee et al. (2016) and Yu et al. (2013, 2018) find no significant difference in design behavior between PDEs and GMEs, suggesting that the influence of environment may depend heavily on individual experience.

Although PDEs show potential for enhancing creativity and expanding design possibilities, they introduce challenges such as steep learning curves (Aish & Hanna, 2017) and black box thinking (Dissaux & Jancart, 2022), limiting the designer's control over algorithms and decision-making processes. The tendency for novices to generate unexpected outcomes (Chien & Yeh, 2012) further underscores the need for educational models that balance exploration with structured learning.

The next sections delve into two critical aspects drawn from this synthesis: the challenges PDEs present for novice designers and the gaps in current educational approaches, followed by an examination of the methodological limitations in existing studies and recommendations for future research.

Challenges of PDE on Novice Designers and Solutions for Educational Gaps

Parametric design is recognized as a fundamental component of current architectural practice, promoting innovation and expanding design alternatives. Despite its significance, parametric design is often introduced at later stages of architectural education, primarily within digital tools and computational design courses (Alalouch, 2018). This delay arises from the complexity of parametric modeling, which requires proficiency in software, scripting, and shape grammar. However, Gürel & Şenyapılı Ozcan (2023) demonstrate that PDEs can also be effectively integrated into the early concept design phase through collaboration with traditional hand-sketching methods. For instance, Alalouch (2018) introduces parametric principles with the "serial of planes" technique to foster early parametric thinking. While this technique effectively builds foundational understanding, it often results in simpler algorithms that lack the complexity needed for

Table 9. Summary of Reviewed Studies (in chronological order)

Study	Test Variable	Collection Method	Evaluation Method	Participants	Design Task	Outcome
(Chien & Yeh, 2012)	Environment	Protocol (PSFIE)	Descriptive Analysis	5	High-rise, Pavilion	Novices produced more unexpected outcomes than experts.
(Yu et al., 2012a)	None (Explorative)	Protocol (FBS)	Descriptive Analysis	2	High-rise Building	Reformulation drives creativity.
(Yu et al., 2012b)	None (Explorative)	Protocol (FBS)	Descriptive Analysis	2	High-rise Building	Model captures most design activities.
(Yu et al., 2013)	Environment	Protocol (FBS)	Descriptive Analysis	3	Shopping Mall, Community Center	No significant behavioral difference.
(Lee et al., 2013)	Experience and Environment	Protocol (PPC)	Descriptive Analysis	4	High-rise Building	'Generation' and 'Changing Parameter' linked to divergent thinking.
(Lee et al., 2015)	Experience and Environment	Protocol (PPC)	Descriptive Analysis	4	High-rise Building	Experts scored higher in creativity assessments.
(Yu & Gero, 2016)	Environment	Protocol	Markov Model	8	Shopping Mall, Community Center	More design patterns used in PDE than in GME.
(Lee et al., 2016)	Experience	Protocol (PPC)	Linkography	4	High-rise Building	No significant difference in cognition or spatial language.
(Aish & Hanna, 2017)	Environment	Personal Experience	Learning Curve	-	Curve Control	Different software shows varying learning paths.
(Alalouch, 2018)	Experience and Gender	Survey	Mann-Whitney U	57	Vehicle Stop	Gender has no effect; software knowledge enhances learning and imagination.
(Yu et al., 2018)	Environment	Protocol (FBS)	Descriptive Analysis	8	Shopping Mall, Community Center	PDE potentially enhances design creativity.
(Lee & Ostwald, 2019)	Experience and Environment	Protocol (PPC)	Linkography	6	High-rise Building	Entropy analysis measures cognitive complexity.
(Namoun et al., 2019)	Experience and Environment	Interview	T-test	24	Website	Novices preferred PDE; experts found tools limiting.
(Lee & Ostwald, 2020)	Experience	Protocol (DMP)	Descriptive Analysis	6	High-rise Building	DMP develops three creative loops in PDE, representing creative processes.
(Dissaux & Jancart, 2022)	None (Explorative)	Interview, Protocol	Descriptive Analysis	18	Pedestrian Bridge, Pavilion, High-rise	Participants relied on videos; assistants as last resort.
(Yang et al., 2022)	None (Explorative)	Survey	Regression Analysis	110	Music Playback Equipment	Model generates 3D sketches quickly.
(Gürel & Şenyapılı Ozcan, 2023)	Environment	Protocol (PPC)	Mann-Whitney U	6	Shelter	Increased cognitive actions in PDE vs. sketching.
(Öztürk Kösenciğ & Özbayraktar, 2024)	Environment	Protocol (FBS)	Linkography	11	Pavilion	Sketching enhances synthesis, PDE diminishes it.

advanced design processes. Determining the optimal stage to introduce PDEs in architectural education remains an important area for further exploration.

Managing cognitive load is one of the most significant challenges in parametric design education, particularly when PDEs are introduced in the early stages of architectural training. This challenge arises from the steep learning curve (Aish & Hanna, 2017) associated with parametric modeling and the need to balance conceptual design exploration with technical skill-building. But integrating the technical knowledge required for PDEs into already intensive architectural programs is difficult. Workshops have been proposed as a practical solution for this problem (Öztürk Kösenciğ & Özbayraktar, 2024). By offering intensive, focused environments, workshops allow students to engage directly with parametric tools in a compressed timeframe. While workshops are effective in familiarizing students with PDEs, they may not always provide a long-term solution to managing cognitive overload or support the gradual development of expertise.

In recent years, integrating advanced technologies such as augmented and virtual reality (AR/VR) has been explored as a means to enhance parametric design education. For example, the pARam tool, which combines parametric design with AR, has shown promise in making artifact customization more intuitive and accessible for students (Stemasov et al., 2024). Similarly, AR/VR technologies have been found to improve spatial awareness and design communication, fostering a more immersive and engaging learning experience (Hafizi, 2024). These technological innovations can offer potential solutions for alleviating some of the challenges faced in parametric design education.

Another significant challenge in parametric design education is black-box thinking, often caused by reliance on online tutorials and pre-made scripts (Dissaux & Jancart, 2022). While these resources support self-regulated learning, they risk creating superficial understanding by obscuring the logic behind parametric systems. This reliance can hinder creativity and independent exploration. Educational models that incorporate the dissection and adaptation of tutorial content with expert guidance could foster deeper algorithmic understanding and reduce dependency on external resources. By making the underlying processes transparent, students can develop more flexible and adaptive problem-solving skills.

The creativity gap between novice and expert designers is another critical concern. Experts perform better in PDEs due to their accumulated knowledge and experience, enabling them to efficiently generate complex and innovative designs. In contrast, novices often encounter unexpected solutions (Chien & Yeh, 2012), which, while fostering creativity, may limit progress due to gaps in foundational knowledge. This highlights the importance of balancing technical skill-building with exercises that encourage divergent thinking. Scaffolded complexity and incomplete recipes (Vazquez, 2024), where students gradually progress from basic tasks to advanced challenges, could support this balance. Such strategies provide opportunities for both structured learning and open-ended exploration, accommodating the needs of learners at different skill levels.

In low-resource educational settings, these challenges are magnified by limited access to advanced software, hardware, and trained instructors (Atabek, 2019). To address these constraints, non-digital exercises such as manual shape grammar, physical parametric models, and algorithmic thinking through paper-based activities offer practical and accessible alternatives (Alalouch, 2018). These approaches simulate parametric processes effectively, enabling students to develop foundational skills without reliance on digital tools. For example, physical model-based workshops can introduce essential parametric concepts while fostering creativity and adaptability in resource-constrained environments. Additionally, Gürel & Şenyapılı Ozcan (2023) suggests developing AI-assisted scripting to simplify the coding process, further easing the transition into PDE for novice designers and highlighting this as a promising area for future research.

Addressing the multifaceted challenges of parametric design education requires innovative pedagogical strategies that balance accessibility, technical proficiency, and creative exploration. Workshops, scaffolded learning environments, and non-digital approaches each play a role in equipping students with the skills and mindset needed to navigate the complexities of PDEs. By fostering transparent learning processes and supporting learners at different stages, educators can prepare the next generation of architects to engage confidently and creatively with PDEs.

Limitations of Current Methods and Future Works

The methods employed to investigate cognitive processes in PDE vary widely, reflecting the complexity and layered nature of design cognition. Surveys (Alalouch, 2018; Yang et al., 2022) and interviews (Namoun et al., 2019) are commonly used, yet their reliance on self-assessment and introspection introduces inherent biases. Participants may misinterpret questions, provide socially desirable answers, or inaccurately recall their design processes, leading to results that may not fully capture actual behaviors. Similarly, protocol analysis, while a preferred method for real-time cognitive data, is subject to coding biases and inconsistencies among evaluators. These limitations highlight the need for combining surveys, interviews, and protocol analysis to enhance the validity and reliability of findings. However, few studies (Dissaux & Jancart, 2022; Lee et al., 2013) in this review effectively integrate multiple methods, underscoring a gap in broader research practices.

Protocol analysis remains the most widely adopted approach due to its ability to document design cognition directly through think-aloud protocols and audio-visual recordings. This method provides a granular view of the design process, capturing the sequence and flow of cognitive actions. Compared to self-reporting methods, protocol analysis offers a more objective perspective. However, the quality of the results depends heavily on coding accuracy and methodology. Additionally, (Shealy et al., 2023) have shown that the think-aloud method applied during protocol analysis creates additional mental load, thereby reducing the time allocated for design.

The absence of standardized coding schemes across studies introduces variability, making cross-comparisons difficult. Although not observed in the studies reviewed, the use of biometric data such as heart rate variability (Ignacio & Shealy, 2023) and EEG (Balters et al., 2023) in cognitive research presents an opportunity to improve the reliability of protocol analysis by providing physiological indicators. Future PDE studies could benefit from incorporating these tools to mitigate the risks of subjective interpretation.

A closer examination of protocol models reveals a strong reliance on frameworks like FBS and PPC. These models are instrumental in capturing design cognition, particularly in the iterative workflow characteristic of PDE. Despite their strengths, limitations persist. In Yu & Gero's (2016) study, FBS protocol analysis indicated a higher frequency of function-to-structure (F→S) transitions in PDE compared to GME. However, the study could not determine whether the identified functions stemmed from pre-learned design patterns or novel rule sets developed during the design task. Similarly, Gürel, A., & Şenyapılı Ozcan, B. (2023) found increased perceptual actions in PDE relative to hand sketching, but the underlying cause whether driven by the design environment or individual cognitive styles remained ambiguous. Addressing such ambiguities requires post-experiment interviews and follow-up discussions, as demonstrated by Lee et al. (2013) to distinguish between emergent design strategies and prior knowledge.

The adaptability of cognitive models is evident when combined with supplementary methods such as semantic analysis (Lee et al., 2016) and entropy analysis (Lee & Ostwald, 2019). These hybrid approaches provide a more nuanced understanding of design complexity and variability. However, while Lee & Ostwald (2019) introduces a framework for quantifying cognitive complexity, the dynamic nature of cognitive styles which evolve with experience and task variation complicates the interpretation of data. The lack of established scales and benchmarks further restricts the generalizability of these findings, emphasizing the need for developing standardized measurement tools in future studies.

Several studies (Lee et al., 2013; Lee et al., 2015; Yang et al., 2022; Yu et al., 2018) investigate the relationship between design patterns and creativity in PDE, yet few address the performance of the resulting designs and none address the algorithm quality. The small sample sizes in most studies limit the scope for statistical analysis, resulting in a heavy reliance on descriptive methods. For instance, Yu et al. (2018) found no significant difference in creativity through mean-split analysis, with 30% variance set as the threshold, while Lee et al. (2016) similarly reported no meaningful variation in creativity scores. This suggests that design cognition alone may not directly correlate with enhanced creativity in PDEs. The absence of performance metrics raises questions about the practical implications of these cognitive models, indicating a need for studies that evaluate design output and performance alongside cognitive measures.

A broader issue is the inherent limitation of laboratory-based studies in capturing the macro-cognitive activities and unique creative strategies of designers. As Lee & Ostwald (2020) notes, controlled environments often exclude critical creative processes such as replication, integration, and analogical reasoning. Expanding experimental models to incorporate computational design principles such as combination, transformation, and emergence can help bridge this gap. However, achieving this necessitates new coding schemes and diverse experimental designs tailored specifically to the iterative and generative workflows in PDE.

While many studies compare PDE and GME, the scope of comparison remains narrow. As Lee and Ostwald (2019) highlights, extending these comparisons to include hand sketching (Gürel, A., & Şenyapılı Ozcan, B. (2023)) and digital fabrication (Öztürk Kösenciğ & Özbayraktar, 2024) could provide a more comprehensive understanding of how different environments shape design cognition. Emerging technologies like VR and BIM also present unexplored opportunities for expanding this research. Additionally, despite increasing attention to diversity in design, Gurel & Senyapılı Ozcan (2023) notes absence of studies addressing gender-based differences in PDE like Alalouch (2018). This represents an area that needs further exploration.

Expanding the scope of PDE research through interdisciplinary collaboration, incorporating insights from cognitive psychology, human-computer interaction, and artificial intelligence could lead to more holistic frameworks for PDE studies. This approach would not only deepen theoretical insights but also enhance the practical application of PDE in architecture, industrial design, and engineering. Addressing the limitations discussed here will be essential for advancing parametric design research and fostering more inclusive and adaptable educational models.

CONCLUSION

This systematic literature review highlights the evolving landscape of cognitive research in PDE, identifying critical trends and methodological approaches across 18 studies. While parametric tools foster iterative and generative design processes, the findings reveal gaps in understanding how these environments influence cognitive load, creative performance, and design behavior across varying levels of experience.

The prevalence of protocol analysis as the primary data collection method reflects the demand for real-time cognitive insights in PDEs. However, the limitations associated with self-assessment biases and coding inconsistencies call for more diverse methodological frameworks. Integrating biometric tools and post-experiment interviews could address these challenges by providing objective data to complement subjective feedback.

A significant gap lies in the under-explored area of PDE education, particularly concerning how novice designers develop parametric skills and overcome black-box thinking. Although workshops and short-term learning models provide valuable introductory exposure, long-term strategies that balance technical complexity with conceptual exploration remain underdeveloped. Future studies should focus on scaffolded learning pathways that enable gradual mastery of PDEs while fostering independent problem-solving.

Additionally, research to date has largely centered on conceptual design phases, with limited examination of how PDEs operate during later design stages, such as analysis, fabrication, and evaluation. Expanding this scope could provide a more holistic view of parametric design's role throughout the entire architectural workflow.

Moving forward, there is a need to broaden participant diversity and consider cultural, demographic, and institutional differences in PDE adoption and learning. Exploring gender-based variations, low-resource educational settings, and alternative design environments, such as VR and digital fabrication, can further enrich the field.

Ultimately, advancing research in PDE cognition requires interdisciplinary collaboration that bridges the fields of architecture, cognitive science, AI, and human-computer interaction. By addressing the methodological and educational gaps identified in this review, future studies can drive more inclusive, innovative, and effective applications of parametric design across disciplines.

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