Optimization in Parametric Design Thinking: Are New Models Needed?

Stephanie Bunt
The University of New Mexico, United States
sbunt@unm.edu

Catherine G.P. Berdanier
The Pennsylvania State University, United States

Nathan C. Brown
The Pennsylvania State University, United States

New theoretical models for design thinking have been proposed in the past when a new technology emerges. For example, models of parametric design thinking were developed to explain differences from design thinking with analog tools. Interacting with increasingly autonomous design tools involving optimization may introduce yet a new type of design thinking. This paper identifies key criteria from historical literature that helped distinguish new design thinking in response to progressions in technology. Then, design behaviors from a recent architectural design study involving optimization with parametric tools are analyzed to consider if these criteria are observed. By comparing the design strategies to the established criteria, we discuss ways in which employing optimization may involve a new form of design thinking. Since optimization represents only partial automation compared to future possibilities with AI, we propose areas for future research to further map design thinking when working with optimization tools and beyond.

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Introduction

Optimization techniques have become common in design, particularly in engineering. While optimization has been used in fields such as aerospace engineering for decades, it has only recently gained prevalence in building design. The recent surge of design optimization for buildings is related to increased use of parametric modeling in architecture and architectural engineering, as well as stringent performance goals for buildings. Used in conjunction with 3D modeling and parametric tools, optimization strategies allow a designer to rapidly isolate desirable solutions from a large set of options based on defined variables, performance objectives, and constraints. A design optimization approach may thus build on parametric design by using the parameters as design variables in pursuit of defined quantitative performance goals. A clear example of parametric design in practice is the Morpheus Hotel, for which the design team at Zaha Hadid Architects developed a "comprehensive parametric model [combining] all of the hotel's aesthetic, structural, and fabrication requirements" [1]. Another relevant example for design optimization is the British Museum Great Court Roof [2], which inspired new optimization approaches [3].

By using algorithms to search a design space, an optimization tool can empower the design process by reducing time-intensive analysis and exhaustive iteration [4]. As the list of performance objectives grows, designers increasingly need swift design feedback to make informed decisions. Computers are used to generate this feedback while producing plausible solutions to complex problems. Previous researchers have shown that optimization profoundly influences design action because of its unprecedented speed in searching a parametric space [5], [6] and how it introduces new iterative relationships [6]. However, studies have not demonstrated how using an optimization approach may change design thinking beyond what is known about parametric design thinking (PDT) in general, given that in design optimization, more design decisions may be made independently from the designer.

The designer has been central to any understanding of the design process [7], [8], [9], [10], [11]. Design thinking models center on the role of the designer, focusing on processes of formulation, synthesis, and analysis, though these processes are named differently by various theorists. For example, an early cognitive model of design thinking, Cross's *designerly ways of knowing* [8], [9], [12], defines design actions taken by the designer while linking sketch modification, reflection, and modification in refinement cycles. Schon [10] similarly depicts an iterative *moving-seeing-moving* process involving observation and visual documentation.

This designer-centric lens has persisted across time despite changes in technology from sketching to digital design to parametric tools. Responding to the introduction of digital tools for design, Oxman developed a schema that connects four classes of information with the designer located at the center, who interprets and interacts with each class [7]. Acknowledging the source of information and how it is understood is important in design thinking as some digital tools, like Artificial Intelligence (AI), can make decisions outside of the designer's internal logic. While optimization algorithms are not synonymous with AI, they can rapidly reject designs that do not align with the designer's prescribed goals. Yet they may also risk dismissing a design that achieves qualitative criteria that would have otherwise been recognized by the designer as beneficial. The term *sensemaking* has been used to distinguish aspects of human involvement in AI activities, [13] and can also relate to design thinking involving automated decision-making. While PDT assumes that the designer's knowledge remains central to all decisions [14], optimization strategies may not meet the same criteria. For example, a process involving significant knowledge-based decisions made by a computer might be better modeled with both a designer and AI bot in the center.

It is worth noting that process models for optimization also exist, which tend to emphasize an iterative relationship with optimization tools [6], [15]. Yet these models often show that optimization strongly relies on data analysis for decisions [5] which deviates from traditional methods for analyzing architectural design options. It is thus difficult to distinguish whether working collaboratively with an optimization process represents another technology-driven evolution in design thinking.

In response, this paper discerns previous criteria in the literature that helped encourage the creation of new models of design thinking. These criteria were previously used to distinguish parametric thinking and digital design from traditional methods, constituting novel leaps in design thinking. We then compare design behavior of building designers when performing optimization, collected from a new design study, to discuss how interactive, iterative optimization may show new forms of design thinking. This research is a first conceptual step towards better understanding how design decisions are made with optimization, primarily at the level of theory testing rather than theory development [16]. With the increase of automation in the architectural design process, it is important to continually challenge our understanding of designer autonomy and inform future models that will describe AI-assisted design.

Background

Over time, design research has established theories for design process while continually challenging existing models as new technologies are introduced. Digital tools, which change how collaboration occurs, how expertise is shared, and how reflection relates to action, have been important in design theory development. However, Cash posits that across publications on design research, there are disagreements about how to best address research impact and theory development [16]. According to Colquitt and Zapata-Phelan, theory has explanatory and predictive power, but its development requires both theory building and theory testing at various levels [17]. Within this framework, our paper tests the edge of current theory, while considering if additional theory building is warranted for the specific instance of using optimization in early conceptual design. To explain our approach, we first review relevant models of design thinking.

Models of design thinking

Design thinking can be defined as "a process of exploration and creative strategies" [14] and many researchers have described design process through diagrammatic models [18], [19], [20]. Early models of design varied in terminology but established a general structure of problem/situation formulation, synthesis/generation, representation, and evaluation. A designer may cycle through these steps, iterating their ideas. Additional models have added context, such as Gero and Kannengiesser's Situated FBS Ontology [11], which accounts for the conceptual space in which decisions are being made. This model has been useful in defining behaviors in different design disciplines [21], [22] and in digital design interfaces [23], particularly with the integration of technology in design.

With increased use of digital tools in design, researchers have established distinctions between digital design and computational design. From an extensive literature review, Caetano et al. states that *digital design* is "the use of computer tools in the design process," [24] whereas *computational design* entails the use of computation to develop designs [24]. Caetano et al. explains that computational design does not depend on digital tools, as in work by Frei Otto. Nevertheless, the use of computers has impacted how designers think about their designs. In 2006, Oxman established that there is a need to reassess theories and methodologies in response to digital design's growing integration in design practice and to guide future research [7]. She developed a schema to describe design information relationships between representation, generation, evaluation, and performance, with the designer at the center of all decisions. From this model, she argued that digital technologies prompt a new type of design thinking. With the growing integration of design with technology, she continued to investigate designer thinking while extending into parametric design.

Models of parametric design thinking

Oxman defines parametric design as "a formation process of parametric structures of associative geometries that generates the geometry of desired objects of design" [14]. Leach has a similar definition, suggesting that a significant change from traditional methods to a parametric approach is the focus on a design "logic" rather than a design "object" [25]. Broadening thinking beyond traditional aptitudes, Woodbury acknowledges that parametric design requires the skills of a designer, mathematician, and computer scientist [26]. In Stals et al.'s model of the parametric process, the "emergence of a concept" and development of a "parametric definition and exploration" are split into two phases with exploratory amplitude cycling in greater variation compared to traditional tools [27]. These concepts have been tested through research. Yu and Gero compared Parametric Design Exploration to Geometric Modeling Exploration and identified that in the early design stage, parametric processes focus more on solutions than formulating the problem [28]. They concluded that, with support from additional literature, parametric thinking is beneficial for solution exploration and supportive for creativity.

In the paper defining PDT, Oxman establishes several axioms to differentiate PDT [14]. It is a distinct design approach in that it can create something that is otherwise unachievable by paper-based means. In PDT, the designer also requires skills in scripting, or writing code, which provides a new way of design thinking. Oxman diagrams PDT as an intersection of the research fields "parametric models of design," "cognitive models of architectural knowledge," and "computational models of digital design process" [14]. Oxman goes on to describe how different applications of parametric thinking can be categorized by her generic schema of process models [7]. She concludes that "design research in this area should become more strategic, computationally informed, and performance-based; it should be oriented to the production of knowledge relative to specific programmatic and functional requirements given by specific contexts" [11, p. 37].

Optimization in architectural design

While Oxman's schema considers some approaches that could be called optimization, the term "optimization" can be broad or narrow in different fields, ranging from architecture to engineering to pure mathematics. Although optimization can generally refer to "finding the best possible solution by changing variables that can be controlled, often subject to constraints" [6], a human interpreter is assumed to interpret the results in many design models. From an engineering design perspective, Martins and Ning presents a model comparing the optimization process to a conventional process [6]. They say that in optimization, a designer may ask "is optimality achieved?" as a separate question from "is the design good?" to guide their next design steps. These two questions address quantitative and qualitative goals, suggesting that an optimization tool cannot dictate the final solution without a designer's interpretation. This idea is also supported in architectural design by Canestrino: "optimization can be traced, with extreme synthesis, to the search for maximum (or minimum) points of certain functions associated with a design's performance" [5]. This definition emphasizes synthesis of ideas, acknowledging the role of the designer and non-explicit criteria, even as optimization possibly enhances or even overly constraints their process.

Optimization involves mathematic functions, with researchers historically using extensive numerical models to implement optimization methods [29]. In building design, it requires designers to configure a design space and solution space, often through a parametric model. Following algorithmic processes, designers can account for multiple performance goals, such as daylight [30] and structure [31], to find a "best" option. However, quantitative objectives are often inversely related, and a clear solution is not always obvious. A designer must analyze and interpret the information returned to them to best influence their design decisions. In optimization, designers may take on the role of data analyst, drawing on skills not traditionally associated with building design. Canestrino states that optimization is dependent on large amounts of data [5]. While it may be tempting to let automated processes parse this data and solve design problems to save time, Canestrino warns that this naïve view of optimization may restrain design exploration to the pre-determined model.

Canestrino also acknowledges that there is a conflict in addressing a designerly knowledge of aspirational design solutions and numerical performance [5], referencing Sigfried Giedion's observation of "the schism between architecture and technology" [32]. Canestrino states that to "access the possibility of an automated optimization process, [designers] must necessarily design in a certain way, opening up many opportunities given by digital tools but also losing many others" [5]. By selecting a discrete point on a graph of performance objectives that seems "best," optimization may reduce flexible topological thinking in design exploration that is characteristic of parametric thinking [14].

Instances of this behavior in optimization align with Caetano et al.'s description of *algorithmic design*, which is not synonymous with parametric design [24]. Caetano et al. explains that the terms Parametric Design, Generative Design, and Algorithmic Design are often used in parallel and confused with one another in literature. It defines the three terms in a layering pattern, with *parametric design* as a broader "approach that describes a design symbolically based on the use parameters" [24]; *generative design* as more autonomous descriptions than parametric design; and *algorithmic design* as a subset of generative design that "focuses on the envisioned design at the expense of producing fewer surprising results" [24] with a finer degree of control. When working in automated processes, designer autonomy is of concern. This concern for designer autonomy, and the models that center it, begins to appear even with simple optimization and only grows with increasing reliance on AI in design [33]. Opportunities for AI to improve sustainable building design processes have been identified [34], so it is important to better understand how automated processes influence design thinking.

To summarize, despite ample design research, a lack of continuous theory building and theory testing can hinder theory development over time [16]. As an initial step towards extending theory of design thinking with the incorporation of automated methods, we identify criteria used in past research that signaled new design thinking. These criteria may help us determine if optimization techniques introduce novel processes in design thinking, particularly for conceptual building design, even if this is not true of all processes that use optimization strategies.

Method

In this section, we first consider which criteria have been used in past literature to define digital design and parametric design as novel processes, with new types of design thinking. We then review the optimization-related design behaviors and strategies identified in a recently conducted design study against these past criteria to discuss optimization in the context of architectural design.

Criteria for a parametric design as a novel process

Previous researchers have established novel approaches to design thinking in digital design and parametric design [7], [14]. Table 1 presents an overview of the criteria used for establishing the progressions in designer-technology models of design across the literature, as we identified them. One distinction requiring new models of design is when *the role of the designer changes*. Rather than designing a building alone, like in traditional methods, parametric modeling prompts the designer to design code and logic. In scripting a parametric model, the potential building becomes a series of associative relationships in lieu of static individual elements [14], [26]. This change in the designer's role also influences a *shift in the exploration of problem- and solution-spaces* in CAD modeling [35], with parametric coding [27] magnifying the iterations for consideration. With this shift in design thinking, the designer's analysis of their design also changes. Designers begin to review a matrix of options rather than discrete, single objects [14], [36]. By displaying an array of options, novel approaches to design thinking also *produce solutions not previously achievable*. Oxman [37] observed that digital design transformed how design could be achieved, while Aish & Bredell [38] identified that parametric modeling allowed a designer to envision an idea beyond traditional methods. Notably, as the design thinking models progress with technology, *the designer remains central to the design decision process* [14]. Cross established that designerly decisions are anchored in designerly knowledge and that a designer will work through complex iterative cognitive processes using introspection and reflection [8], [9]. For an optimization process to require a new model of design thinking for explanatory and predictive accuracy, these criteria will likely also be present while working with the new technology. If optimization in building design introduces a new model of design thinking, then a new theory is necessary to understand and explain design behavior in optimization processes.

Table 1 Table of criteria to define a new model in design process thinking.

Criteria	**Citation**
The role of the designer changes	Stals 2021; Oxman 2017; Woodbury 2010;
Shift in solution exploration and analysis	Stals 2021; Oxman 2017; Reas & Fry 2014; Davis et al. 2011
Produce a design not otherwise achievable	Aish & Bredella 2017; Oxman 2006
Designer remains central to decisions	Oxman 2006; Cross 2006; Schon 1983; Cross 1982;

Optimization strategies

To better understand optimization strategies in early conceptual building design, we conducted a study that considered the behavior of 19 participants in response to an optimization design task. In the study, 10 design graduate students and 9 practitioners in building design professions were asked to develop an atrium solution for a fictional client in the Southwestern United States. All participants had experience modeling in the study's primary design tools (Rhino for 3D modeling and Grasshopper for parametric scripting) and were able to employ optimization strategies. The students were required to have completed one course in optimization with at least six months of experience in Grasshopper, and the practitioners had to have completed at least five projects using optimization techniques in practice. The participants were provided with a base Grasshopper file with site context for their design and were required to consider the visual appearance of their design. They were also asked to account for two of three performance objectives of solar radiation, daylight, and structural stiffness. They were provided with pre-built rapid simulations for these objectives.

Participants were asked to employ optimization but were given freedom to select a plug-in or algorithm of their choice. In the digital tools, using an optimization tool to search a parametric model requires the designer to specify the variables and objectives to be searched and is initiated by the designer clicking a "run" button. While the tool "runs" the optimization process, it also rapidly displays the geometric models of the tested iterations in the modeling space. The designer may stop the optimization search at any time or let it complete the search based on specified constraints and stopping criteria. The designer can then review the "best" performing options and either select one or continue to edit the model. At the end of the design sessions, the participants presented 1-2 design proposals for the client.

During the design sessions, the eye movements and screen recordings of the designers were captured, and established methods for documenting design processes were used to code optimization behavior. Since the designers were moving between their internal ideas, expressed ideas, and interpreted ideas through the design interfaces, we used Gero and Kannengiesser's Situated FBS Ontology [11] to develop the codebook and describe distinct cycles and more comprehensive behaviors. In a previous paper on designerly behavior [39], we identified 3 types of optimization cycles: a Complete Cyle where the designer reviews the design feedback from the optimization tool and edits their design, a Coarse Cycle where they review the results from the optimization algorithm but does not respond to the feedback, and a Partial Cycle in which the designer uses an optimization tool but does not review the suggested performance feedback from the tool. These cycles revealed unexpected uses of optimization tools that were not exclusively quantitative, and thus did not necessarily follow established process models for design optimization, like Martins and Ning's diagrams of the optimization process [6]. Some incidents of Coarse and Partial cycles also lacked “extreme synthesis,” as Canestrino [5] required in defining architectural optimization.

Results

From the design sessions captured in our study, we found that optimization strategies vary, and that resultant patterns of design thinking may not exhibit our criteria for a novel model of design thinking. In addition, while optimization may support decisions, it may not always change how a designer thinks about a problem.

Overview of the iterative cycles from our study

Previously, we identified three optimization strategies including Complete, Coarse, and Partial Cycles [39]. With the inclusion of more participants, we also identified an option in which a designer chose not to use an optimization tool at all, which we call an Independent Cycle. Figure 1 shows a diagrammatic representation of their strategies and indicates the number of participants represented by each cycle type.

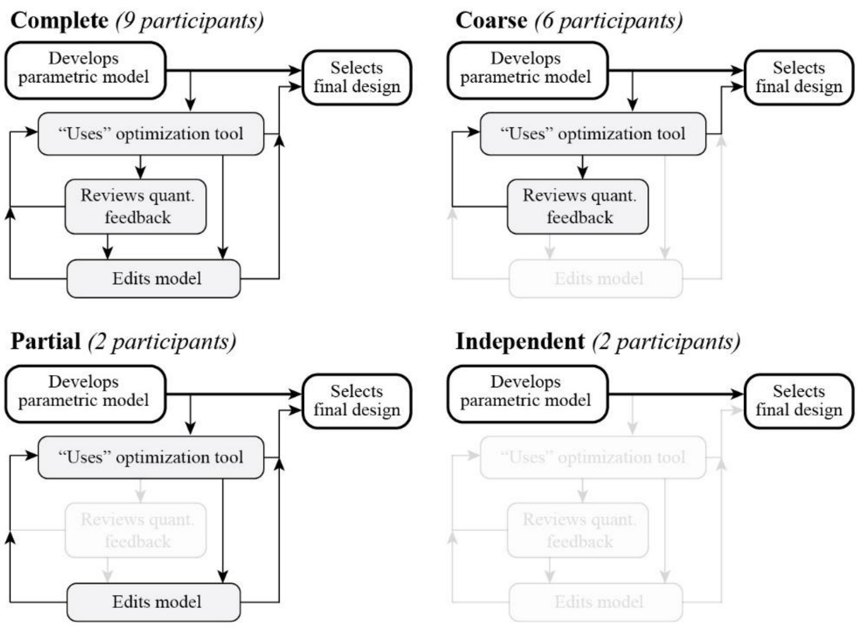

Fig. 1 The complete, coarse, partial, and independent cycles of optimization strategies identified and how many participants aligned with each cycle type.

Complete Cycle – In a complete cycle, the designer reviewed the quantitative “best” options from the tool, edited their model in response to feedback, and used the optimization tool again at least once. This represents thorough use of the mathematical advantages of an optimization tool, using suggestions from the tool to not only “select” a design, but to inform further exploration or modifications to the associative relationships in the model that can lead to even better performance. However, while some designers eventually selected a final design from the optimization suggestions, a few changed the design slightly from the “best” option to meet a qualitative goal based on the designers’ knowledge. Some designers exhibited a Complete Cycle but constructed their parametric model to have little variation in its geometric characteristics, reducing design options before using the optimization tool.

Coarse Cycle – A coarse cycle represents that a participant “ran” the optimization tool, reviewed the “best” suggestions, but did not edit the model in response to the feedback. Participants who had design sessions in this category often ran the optimization tool only once and did not exhibit “extreme synthesis” [5] of their design. This is an example of when optimization strategies may reduce flexibility in design thinking as the designer selects the discrete point on a graph that seems “best” rather than exploring options. In the context of a design study, however, the participants may have been less inclined to iterate an idea due to external time constraints or perceived expectations. They may also have viewed optimization as a final step in their process and not an integral part of their decision making.

Partial Cycle – In a Partial Cycle, the designer initiated a search with the optimization tool, but either did not review the tools suggestions or stopped the optimizer before it completed. While a Partial Cycle may indicate a designer’s oversight on using the tool, there were also sessions when a participant used the optimization tool to review the extents and potential designs generated from their parametric model. One participant mentioned after initiating the optimization search that their model did not have the range of visual solutions that they desired, so they stopped the search to edit their model. Another observed that two variables, which controlled the shape of their atrium, caused the structure to flatten and disappear when the optimization tool drove to certain solutions. This participant repeatedly ran the optimization tool and edited the model to account for unexpected errors before letting the optimization tool run a full search. Both are examples of using an optimization tool as a mechanism to learn about their parametric models, not necessarily find an improved final design. In addition, a participant who did not review the suggestions from the optimization tool did not engage with the data analysis step of an optimization process. We did not expect to find a strategy that used an optimization tool without the designer's interest in the performance of the model, since optimization primarily benefits quantitative searches. However, the optimization tools often used in architectural design provide visual feedback as well as numeric and may prompt design thinking different from other professions.

Independent – Two participants chose not to use an optimization tool in developing their solutions. While the participants were aware that the study focused on optimization, the design prompt did not explicitly require an optimization technique. One participant disregarded the formal design objectives, stating that they would consider those values at a later stage in project development, and they were more interested in passive sun strategies in the conceptual stage. The second participant wanted more control of their final design rather than subjecting their model to an optimization search and chose to manually check the objective values for an improved solution, balancing qualitative goals with quantitative performance. This act suggests that using an optimization tool, from the perspective of this participant, would relinquish some of their autonomy as a designer.

Comparing optimization behaviors against criteria for new forms of design thinking

For each of the criteria that we identified, we discuss how those working with optimization show or do not show a new type of design thinking.

Role of the designer changes – In optimization, the designer is still a coder of variable relationships as they are in parametric design. However, as observed from our study, optimization tools allow a designer to rapidly test the boundaries of their parametric model while not necessarily focusing on a final design. In this way, the designer is more like a data analyst, which requires them to conduct a "process of inspecting and modeling data with the intent of discovering useful information, informing conclusions, and supporting decision-making" [40]. This was evident in several participants. One participant, who used the optimization tool to reveal errors in the model and edit the variable bounds, was informed by the feedback data. In addition, several participants following Complete Cycles reviewed the Pareto front from their optimization search, interpreted the results for their qualitative and quantitative merits, and made informed decisions in selecting a final design. Although there is a change of the designer's role to include data analyst, a distinct shift in the exploration of solutions is less clear.

Shift in solution exploration and analysis – A marked difference between traditional design methods and parametric modeling is that the designer reviews an array of diverse options rather than a few at a time [14], [36], and thus can think topologically in terms of gradients rather than typologically.

Optimization tools also display an array of options within the parametric space, which does not separate them from parametric modeling. In addition, the behavior of several participants followed Caeterno et al.'s definition of *algorithmic design* which "focuses on the envisioned design at the expense of producing fewer surprising results" [24]. In this way, algorithmic design is a subset of parametric design, but may restrict design thinking.

For several participants, the visual variation of final solutions was subjectively small, and exploration of options was limited. This characteristic of the model reduced advantages afforded by optimization searches. For example, in models that generated more variation of geometric or design properties, the "better" performing options were informed by the optimization search without the designer searching the performance space on their own. Since the designer does not need to limit the design space to manually account for less desirable options, a model that is built to incorporate optimization may produce more unexpected solutions. However, the designer's efforts towards a final design may not always be informed by the optimization tool's quantitative feedback, as we observed in Coarse and Partial Cycles. Regardless, in reviewing optimization results, it is valuable for the interface displaying performance objectives and design options from an optimization tool to clearly communicate information for rapid interpretation. Many tool developers have created optimization tools with graphical interfaces, such as Galapagos [41], Wallacei [42], and Octopus [43], which display data feedback with customizable visual aids. The introduction of tools made specifically to provide better data feedback also supports the expansion of the designer's role to include data analyst.

Producing a design not otherwise achievable – While optimization tools increased speed of performance-based design exploration beyond what is achievable in parametric tools alone [5], the designs are still contained in the limits of the original parametric design space, unless the parametric script itself was updated. Optimization might find a high-performance design that is unlikely to ever be uncovered by a manual search, but this is difficult to judge within our design study since each parametric model was custom-built by the participant. In the study sessions where the designer used the optimization tool to learn about their model, a novel design process is plausible. However, in design sessions where model variation was limited geometrically, the parametric model did not reveal new options and the use of an optimization tool was somewhat superficial.

Designer remains central to decisions – While the use of an optimization tool and response to its feedback is at the discretion of a designer, several Independent Cycle participants were concerned with how an optimization tool may remove their design autonomy. Those participants expressed that using an optimization tool in the conceptual design stage would limit their goals and control of the model. In addition, while the optimization tool can rapidly provide improved solutions, it may also dismiss options that the designer's "knowledge" may have identified, removing decisions from the designer. There were also participants in the Partial Cycles that did not review final options but selected the "first" option from the optimization tool by default. These participants did not perform any synthesis of their design after optimizing, suggesting that optimization processes may not hold the designer central to all design decisions in all instances.

In summary, while optimization may qualify as a unique design process in some ways based on previous evolutions of design thinking, the use of an optimization tool does not guarantee a unique or improved design process. In addition, the use of an optimization tool may make designers feel more limited than empowered and behave accordingly. With increasing use of computers to aid in rapid design development, in the future it may be beneficial to consider the computer as an autonomous agent alongside the designer, and update models accordingly, but that is not necessarily the case for optimization.

Discussion: A proposal for future updates

Based on these findings, we propose potential expansions to existing theories, as well as to the criteria in this paper. Historically, with each proposal of a new form of design thinking, a new field of research was introduced. We consider a new category in the progression in design thinking in Figure 2. We borrow language from Oxman's diagram of PDT [14] to describe the stages and reframe the historical development of a design thinking that incorporates optimization. Initial research into Traditional Design Thinking (or design thinking using traditional, non-digital tools) focused on Cognitive Models of Architectural Knowledge, such as Cross' *designerly ways of knowing* [9]. With the introduction of digital tools, research on Digital Design Thinking included Computational Models of Digital Design Process, such as Oxman's 2006 work Theory and Design in the First Digital Age [7]. For research in PDT, Oxman includes the field of Parametric Models of Design. Oxman's resulting work in modeling digital processes was foundational to our own understanding of design behaviors when working with parametric design optimization tools. While optimization allow for explaining generative and form finding models that bypass the designer before presenting results back to the designer in the center, there may more opportunities to expand the theory to include the computer as an autonomous agent. Future diagrams could be more explicit about how the designer and computational agent relate to one another, often mediated by more significant data analysis and visualization tools than were common in early parametric software.

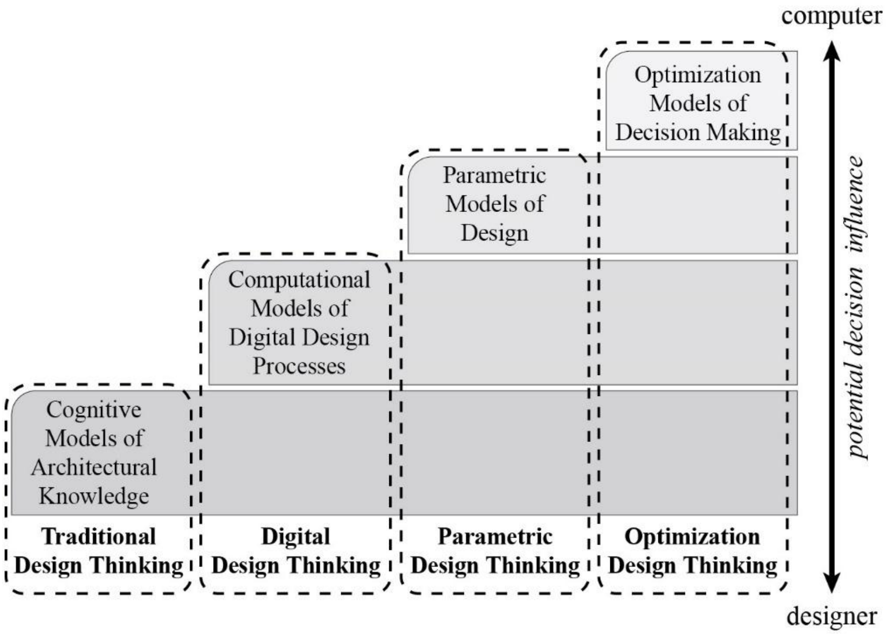

Fig. 2 Intersecting research fields evolving to Optimization Design Thinking

While optimization is dependent on parametric relationships, it requires substantial understanding of an additional field of knowledge to be implemented successfully. Therefore, we consider *incorporating a new field of research* for determining an evolution in design thinking: Optimization Models for Decision Making. This specific field of research is less clearly defined, although research in design decision-making is extensive and researchers are already considering the impact of AI assistance on optimization and decision making [33], [34], [44]. While much literature discusses approaches to optimization [4], [6], [29] and others model optimization as a design process [15], [45], we propose future research that focuses on the influence of optimization strategies on design thinking.

Within Optimization Design Thinking, a designer may follow expected procedures to produce an optimization informed design, like in Martin's model of an optimization design process [6]. Alternatively, there could also be unintended consequences of using optimization in design, as we observed in our study. In our empirical study, not all participants used optimization tools to explore their model for quantitative characteristics, some instead using the tool as an idea generator or parametric script checker. In addition, some participants chose not to use the optimization tools at all at risk of losing their autonomy. While optimization tools help direct a designer's focus by parsing undesirable solutions based on criteria established by the designer, it may also discard unanticipated solutions that the designer would want to consider. Although optimization is not synonymous with AI, the increased incorporation of automation in design requires us to account for changes in design thinking that may move away from designer autonomy.

Limitations

Optimization processes can occur in any field and proceed with many different computer tools, so the outcomes from our theoretical assessment in our design study may vary by other tools or professions. In addition, the use of optimization techniques over the full development of a design project in practice may elicit different behaviors. However, we provide a basis for discussion in theory testing and development, based on our previously defined design behaviors when working with optimization tools. In addition, we acknowledge that others may interpret the criteria for needing a novel model of design process differently. Our list was established based on what we consider to be leading researchers in the area, and it could be further discussed and expanded in future publications. Our qualitative design study does not reach the level of statistical significance regarding the prevalence of certain behaviors, but we aimed to explore our list of criteria against what we observed, rather than making sweeping conclusions about all designers who use optimization tools. Each participant represents a rich amount of data for this type of interpretation.

Conclusion

With the ever-growing use of computer technology to help in producing and improving design solutions, it is important to maintain our understanding of the design process. Optimization tools can vastly improve our design efforts for better buildings, but they may also challenge how we understand design autonomy. This paper seeks to stimulate potential pathways for future theory testing and development around situations in which computation is transitioning from *design tool* to *design partner* [33], of which using optimization is only an initial step. Future models to describe design thinking involving optimization can consider the changing role of the designer, who must increasingly analyze large amounts of design data, and weigh the potential for creating designs that were not previously possible with shifts in designer autonomy.

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