Generative Design: Reframing the Role of the Designer in Early-Stage Design Process

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Generative design tools empowered by recent advancements in artificial intelligence (AI) offer the opportunity for human designers and design tools to collaborate in new, more advanced modes throughout various stages of the product design process to facilitate the creation of higher performing and more complex products. This paper explores how the use of these generative design tools may impact the design process, designer behavior, and overall outcomes. Six in-depth interviews were conducted with practicing and student designers from different disciplines who use commercial generative design tools, detailing the design processes they followed. From a grounded theory-based analysis of the interviews, a provisional process diagram for generative design and its uses in the early-stage design process is proposed. The early stages of defining tool inputs bring about a constraint-driven process in which designers focus on the abstraction of the design problem. Designers will iterate through the inputs to improve both quantitative and qualitative metrics. The learning through iteration allows designers to gain a thorough understanding of the design problem and solution space. This can bring about creative applications of generative design tools in early-stage design to provide guidance for traditionally designed products. [DOI: 10.1115/1.4056799]

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1 Introduction

New developments in artificial intelligence (AI) offer designers new tools that can be integrated into the design process [1]. These tools have been used by designers in many stages of the design process, from the early stages of need finding [2], brainstorming [3], and concept generation [4,5] to later stages of design evaluation [6,7] prototyping [8] and production [9]. This collaboration between designer and AI tool throughout the design process opens opportunities for approaches which vastly open up the space of possible designs beyond what human designers can generate.

Generative design tools empowered by the advancements in AI are increasingly being used in industry and research applications to augment the design process. Generative design tools use algorithms to process designer-set specifications to create a system for design that can generate and optimize computational designs that meet functional requirements [10–13]. Often, the designs generated contain shapes that are difficult for human designers to create or perfect on their own. While these tools were originally used to evaluate and optimize products in the later stages of design, the latest wave of computation tools driven by AI has allowed them to be used for early-stage design [1]. Recent research suggests that the use of generative tools in early-stage design can assist designers in more creative tasks, such as ideation, to generate unique and complex designs [14].

Generative design has the potential to change the traditional design process and yield products that surpass their original performance. There are many examples in both research and industry where generative design tools were vital in generating high-performing products. For instance, General Motors used Fusion 360 Generative design to redesign a seat bracket. Using the tool, the designers were able to produce a bracket that was 40% lighter and 20% stronger than the original part while also consolidating eight of the bracket components into one 3D printed part [15]. This showcases the potential for generative design, in which the strengths of human designers and AI can be combined to produce high-performing results. At the same time, there is still much to understand regarding how these computational tools might change designers, their behaviors, and the product design process.

This research project aims to provide key insights into the interactions between human designers and generative design tools within the design process.

> *RQ1: How does the use of generative design tools in product design impact the design process?*

In generative design, some tasks traditionally done by human designers, such as concept generation and product optimization, can be passed on to the generative design tool. This may significantly change the way designers approach the design process. Rather than thinking about how to create several one-off designs, designers may consider how to create a *system* for design that would allow the design tool to generate a large number of valid outputs. This can involve setting the appropriate specifications, manufacturing methods, and product architecture early in the process to input into computational tools.

> *RQ2: How does the use of generative design tools affect designer behavior and approach to the design process?*

The inclusion of computational tools in design can influence the behavior of human designers, such as communication between designers and confidence of designers throughout the design process [16–18]. Similarly, the behavior of human designers can affect the performance of computational tools. For instance, some aspects of design parameters cannot easily be quantified for the generative design tool, such as aesthetics, so designers may alter the generated designs to be more aesthetically pleasing. This subjective

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decision, which differs between designers, can result in different design outcomes between designers to common design objectives [19].

This study involves interviewing designers about the strategies they have employed in their design process while using generative design tools and takes a grounded theory approach to analyze collected data and identify key themes. While there are numerous generative design tools, many of which are custom-made for industry or research use, this study focuses on commercially available generative design tools developed by widely used computer modeling software including Autodesk Fusion 360, NTopology, CATIA, and Rhinoceros.

2 Background

2.1 Generative Design. Generative design involves the collaboration of human designers and algorithmic computation to achieve complex goals with superior results than that of each entity when creating independently. Generative design tools in the design process can take on many forms with varying levels of involvement from the tool [20]. The design process can be driven by the designer, with minor involvement from computational tools in tasks such as ideation or analysis. For example, Autodesk DreamSketch uses a generative design algorithm to produce multiple 3D sketches based on a designer's initial problem definition [21]. On the other hand, the generative design process can have more substantial tool involvement, as is the case with many commercially available generative design tools. Designers input design goals and specifications into the tool. The tool will explore possible solutions and generate several valid designs that meet the requirements. In this process, generative design tools can be used to take on many tasks in the design process, including idea generation and product optimization. An example of a product created using generative design tools is shown in Fig. 1.

Generative design in which the design tool takes on a more active role has the potential to drastically change the design process while leading to more creative geometries [10]. Therefore, this research focuses on generative design where the optimization tool takes on a larger function in the design process.

No consistent process for generative design has been outlined in detail in previous literature. Some design processes have been suggested in previous research or by companies that create generative design tools [22,23]. However, these processes focus on the tools' role in the process rather than on the role of the designers. The study described in this paper is grounded in the actual experiences of designers using generative design tools to propose a detailed generative design process that considers the role of the designer and the optimization tool.

2.2 Tools in Generative Design. The use of generative design tools has been increasing in research and industry. Buonamici et al. used Autodesk Fusion 360 generative design to create several designs of a robot gripper arm and compared them to those made by designers using topology optimization tools [12]. The designs created by the generative-driven tool yielded performance on par with designs made by designers and traditional optimization tools.

While generative design tools can be used throughout the design process, they have recently been shown to be effective in early-stage design in particular [14]. Lopez et al. compared simple line sketches created by generative design tools and human designers. They found deep learning generative design tools have the potential to generate functional ideas and aid designers in early-stage design tasks such as ideation. Vlah et al. applied topology optimization and generative design studies within the Autodesk Fusion 360 software to an industrial case to understand their suitability in early-stage design [24]. They found that defining the design to be used in generative design tools requires engineers to adopt a different approach in setting up the design space. Computational tools can be used to influence aspects of early-stage design, such as aesthetics, generating designs with specific shape grammars through parametric models [25].

Recent research focuses on developing computational tools and evaluating the design outcomes of optimization tools. However, the way these tools are utilized within the product design process can also have an effect and incorporating these tools into practical design processes can be a challenge, including identifying instances for automated versus manual tasks and understanding how to incorporate generative design tools within more traditional product development processes [26]. Therefore, this research aims to understand how generative design tools may influence the product design process.

2.3 Designers in Generative-Driven Design. Computational tools in design can influence the designer's cognitive processes, their design exploration, and overall designs generated [16]. It is therefore important to understand the interaction between human designers and generative design tools and their effect on designer behavior.

Using optimization tools in the design process requires designers to adopt different design practices since generative design tools require different stages and considerations in their setup [24]. For instance, parameters defined early on in generative design tools may need to be changed due to aesthetic, functionality, or financial considerations discovered later in the process [27]. Therefore, designers must first be able to adapt to changing requirements that emerge throughout the design process and learn to use different generative design tools accordingly.

Collaboration styles of design teams have been shown to affect the design process and design outcomes. In human design teams using computer-aided design, the speed and quality of designs generated were affected by different collaboration structures and modes of communication between designers [28]. The emotions of human collaborators while using computer-aided design software may also be affected in human design teams [29]. Similarly, the interaction between human designers and artificial intelligent tools, such as

Fig. 1 Comparison of the original engine bracket manufactured by General Electric (right) with an optimized bracket (left) created using Autodesk Fusion 360 generative design

Table 1 Background, generative design tool, and experience using the tool for the six interviewees

Interviewee	Background	Tool used	Tool experience level
1	Industrial designer	Fusion 360 Generative Design	Expert (3 + years)
2	Mechanical engineering designer	Fusion 360 Generative Design	Expert (3 + years)
3	Mechanical engineering designer	Fusion 360 Generative Design	Expert (3 + years)
4	Industrial designer	NTopology Generative Design	Novice (4−6 months)
5	Architectural designer	Design Space Exploration	Proficient (1–2 years)
6	Architectural designer	CATIA Generative Design Engineering	Proficient (1–2 years)

generative design tools, throughout design may also affect the design process and outcomes. Some experimental research has been conducted to investigate the effect on designers of incorporating computational tools into the design process. Bansal et al. investigated the effects of software updates on the AI tool during design. They found that while the updates gave the AI tool higher accuracy, it disrupted the designer's mental model of the tool and could decrease team performance [30]. Cagan et al. examined the impact of abrupt problem changes on AI-assisted design teams [17]. They found that the AI tool improves the initial performance of low-performing teams but the performance of high-performing teams using AI is negatively affected, namely due to the increased cognitive load from using the AI tool and improper designer interpretation of AI suggestions. Their study emphasizes the importance for designers to understand the AI tool used in AI-assisted design and how to apply it appropriately in the design process. Another study looked at the communication structure changes within human-AI teams [31]. The results indicate that the use of AI in the design process leads to both higher communication between designers and greater richness in communication as indicated by diversity, relevance, and cohesion. The design of the AI tool may also influence designer behavior and design outcomes. Pillai et al. investigated the effects of computational tool design on early-stage design exploration [18]. In-lab experiments with novice designers indicated that computational tools affect both how designers interact with the tool and the overall design outcome. Chaudhari and Selva found that interactive deep generative design tools have the potential to affect the designer's learning and understanding of the effects of design features on objective performance [32].

Current research investigating the impact of computational tools on human design teams suggests that the incorporation of computational tools in design can have a positive or negative impact on design outcomes depending on its influence on designer behaviors. However, more research is needed to recognize the extent computational tools affect individual designers and the design process [31]. There is also a lack of understanding regarding the different factors of human behavior that computational tools may influence. This work looks to bridge this gap in the literature by investigating in depth the generative design process and the interaction of generative design tools and human designers throughout the process.

3 Methods

This qualitative research study applies a grounded theory approach, which is a method from social science used to build new theories rooted in collected data [33,34]. This methodology allowed for a thorough understanding of the generative design process to be developed through open-ended interviews of six interdisciplinary designers using various generative design tools.

3.1 Interviews. Six designers in mechanical engineering, architecture, and industrial design were interviewed regarding their use of generative design tools. The interviewees were practicing designers or graduate student designers who use generative design tools in their work. All of the designers interviewed had over 5 years of general design practice. The level of experience using generative tools in their design process ranged from 4 months to over 4 years. Since commercially available generative design tools are relatively new (e.g., Fusion 360 Generative Design was released in 2018), designers with more than three years of experience at the time of the interview were considered experts. A summary of the interviewees is shown in Table 1. Interviewees were recruited through the authors' networks followed by a snowball sampling technique in which interviewees were asked to refer to designers using computational tools to find additional recruits. The interviews were conducted in person or virtually and averaged about an hour long. All interviews were audio recorded, and the use of the design tool was screen recorded.

A semi-structured interview format was used to allow for both breadth and depth of related topics [35]. Each interview consisted of an open-ended discussion on the designer's use of generative design tools. Interviewees were asked to walk through the design process of a product made using a specific generative design tool. The types of products discussed included a robot chassis, automobile components, small brackets, furniture, art installations, and large building structures. These products were made using different generative design tools in commonly used modeling software.

In keeping with the grounded theory approach, each interview was summarized and analyzed for overall themes and design process shortly after the conclusion of the interview [36]. A preliminary design process was outlined after the first few interviews. The overall process remained unchanged through the course of additional interviews. Therefore, the interview process was concluded after six completed interviews as no significantly new information about the overall process was gained from additional interviews [37].

3.2 Transcription & Coding. Audio recordings were transcribed verbatim using automatic transcription software (otter.ai). Transcriptions were reviewed by the researchers and modified to remove any errors in the text, then were imported into a qualitative analysis software (ATLAS.ti). The data was coded by the researcher who conducted the interview, ensuring familiarity with the data and understanding of the themes throughout the text [38]. The first level of coding utilized descriptive open coding, in which the data were segmented into preliminary categories that summarized the topic of the data passage with a focus on the meaning of each statement [37,39]. This open coding technique allowed the first stages of categories to be developed directly from the data and not influenced by an outside set of categories and expectations [36,37]. In the second stage, axial coding was used to organize the codes into broader themes to generate categories and subcategories [39]. For instance, "back of the envelope calculations" and "loading approximations" were coded separately at level 1 and then combined at level 2 into one category of "estimation." This was a subcategory of "Setup method: intuition," which also included the level 2 category of "past experiences." Another subcategory of "Setup method: context" was created from the open-coded categories of "user specifications" and "industry standards." Finally, theoretical coding was used to refine the groups, thematize the categories, and link the categories and subcategories to form an overarching process [39,40]. The two subcategories of "Setup method: intuition" and "Setup method: context" were grouped under the theme of "Constraints" developed at the theoretical level of coding. An example of this coding

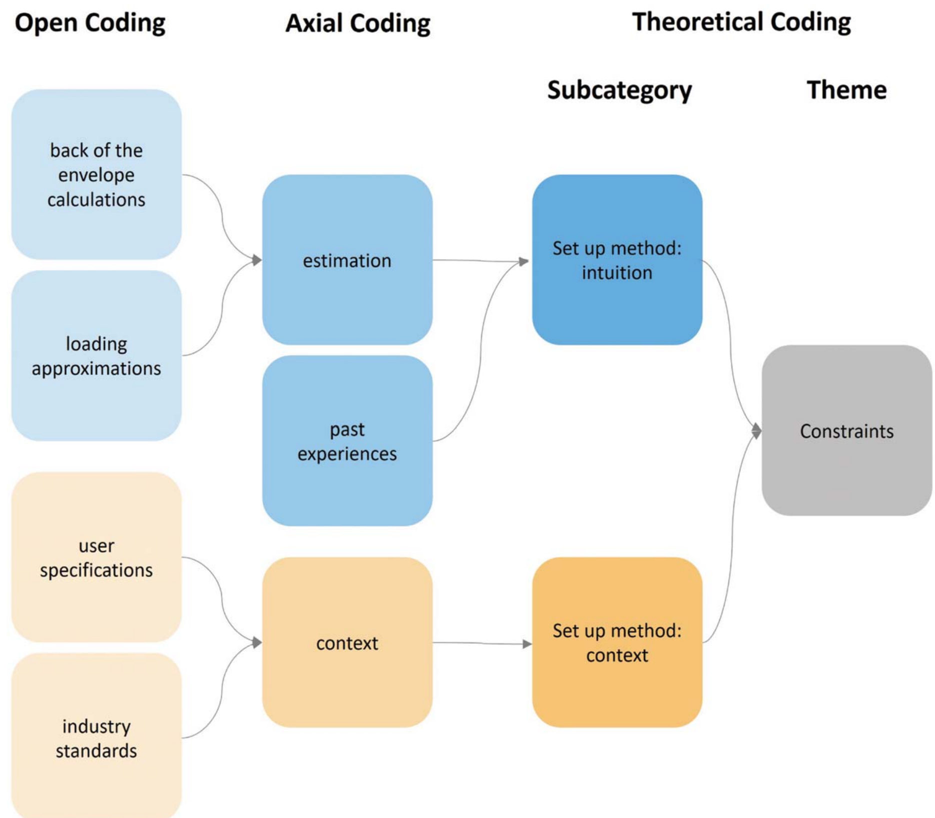

Fig. 2 The three stages of coding used: open coding, axial coding, and theoretical coding. Examples of coded categories from the data under the theme of "Constraints" are shown.

process is shown in Fig. 2. These stages were iterated on until no additional themes emerged. The multiple levels of detailed coding ensured that the theories developed from the interviews all emerged from the data and were not influenced by outside models and expectations [36,38]. Additionally, study participants, design tool experts, and qualitative research methods specialists were consulted throughout the coding process to validate the findings through the analysis [39].

4 Results

The linked codes generated through the analysis of the interviews were used to outline the generative design process as described by all the interviewees. The quotations from the interviews provided in this text are edited to remove pauses, fragmented sentences, and repetitions for ease of comprehension.

Explicit and implicit roles of the designer and generative design were derived through the interviews. Details of the factors considered and the methods in which they were included in each stage were also described in the interviews.

4.1 Generative Design Process. The generative process that emerged from the interviews is shown in Fig. 3. In the first stage, the designer defines the objectives, parameters, and constraints related to the design problem. These are entered into the generative design tool which uses the provided specifications to generate designs. The designer will evaluate the results created by the generative design tool and iterate on the objectives, parameters, and constraints until they are satisfied with the results. The designer then selects from the results and manually refines the design until they reach a final design outcome. Implicit inputs and outputs (such as the designer's expertise and an understanding of the design space) were also uncovered as part of the process. All of the designers interviewed described the overall process in Fig. 3. The details of each stage varied between designers, contexts, and tools. The different details and methods used in each stage, as described by the designers, are outlined in this section.

4.1.1 Define Inputs: Objectives, Parameters, and Constraints. The first step of the generative design process is to define the objectives, parameters, and constraints that the design tool will use to generate the designs. The interviews indicate that the objectives that designers specify in the tool relate to performance metrics, such as minimizing weight or maximizing stiffness. Some projects may require different objectives such as maximizing thermal efficiency of a heat sink or minimizing the embodied carbon of a building to account for the environmental footprint. Parameters are the variables that define the design problem. Some examples of parameters mentioned in the interviews are the material properties, the desired manufacturing method, and the safety factor. The designer must also define the loading conditions to describe the location and magnitude of the forces, moments, shear stresses, etc. Another important parameter the designer must define is the conserved geometries, the features that must be maintained in all the designs generated by the tool. The final input into the computational design tool is the constraints, or limiting conditions, in the design. Some of the constraints defined are linked to the objectives, for instance, a maximum weight constraint for the design. The designer also defines the geometry constraints, referred to by the designers as the obstacle geometries or keep-out zones, where the design generated by the tool cannot extend into.

The values for the objectives, parameters, and constraints are defined by designers in many ways. The designers described deriving the exact specifications from user needs, customer requirements, or industry standards.

> *"In this case, [the constraints] are mostly structural and are for specific building codes. That's also [something that] could be location specific."*

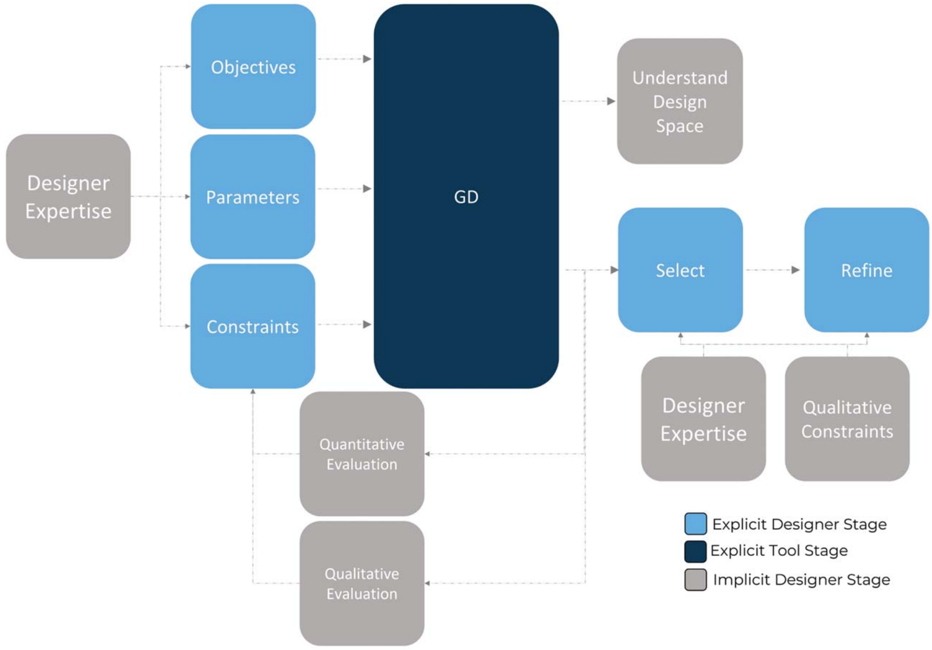

Fig. 3 The generative design (GD) process derived from the design processes described by the interviewed designers

While the precise values of the constraints are not always well defined in the early stages of the process, the designers still find it beneficial to estimate the initial values to start using the generative design tool. Designers may analytically determine the values through quick calculations.

> *"That upward force corresponds to an F = MA calculation. Then we also [considered] what's the deflection when we hit the ground? We roughly approximated that and that's how we got that number. So, there's a lot of back of the envelope calculation."*

Designers can also use their knowledge and experience to estimate the target values for the objectives. They can also set a conservative value in estimating the constraint to ensure the final product meets all specifications.

> *"If we make a stronger [product], we estimate that'll probably add three to four pounds. So, let's overshoot [the value of the weight objective] and see what we can do. And so, we said four to five pounds."*

The estimated values for the inputs are based on the designer's intuition, in which their past experiences and knowledge would allow them to make approximations they believe to be reasonable.

> *"From a structural point of view, if you start distributing the material along its section, you can have lighter structures that perform better from a certain point of view. [But] from a thermal point of view, we know the more surface, this [feature] as a cooling element can be better."*

Designers can also rely on past experiences with similar design problems to inform the tool setup.

> *"What we would do if we had no information [regarding constraints from the client] is actually trying to find information in our own database. From the other [similar products], we could actually try to imagine what it would look like."*

The types of inputs that can be accommodated differ across tools and can be limiting in some instances. For example, some tools only allow for force loads to be added, and any torques or moments applied in the design problem must be represented in alternative ways by the designer. One designer described the limitation of being able to only define static loads, which was not representative of the dynamic and shock loads they also wanted to include.

> *"I just want [to] take this part, and … shake it, and throw it off a building, … I don't know what these four points will be loaded with, but I just want them to be strong enough to hold up. For each of these holes, I had to input six different individual loads."*

The designers interviewed also described some qualitative-related factors that could be considered in the design. Aesthetics and other qualitative objectives were still often mentioned by the designers throughout the design process. When asked about aesthetics consideration in design, one interviewee mentioned that it was subconsciously considered by the designers through the process, but officially it was not defined as part of the project objectives.

> *"I would say non-officially, yes. Officially, no…Officially, we would just say that [the result is] the geometry that just fits the constraint. And that's also what all the people around would expect us to do… the chiefs, experts, clients, and so on. I don't think it has ever been a question about aesthetics."*

Often, these additional qualitative constraints cannot be inputted into the tool directly, so designers find workarounds or manually design these at later stages.

> *"That's not a weight constraint or anything. That's just, we need to make sure our holes are smaller than a certain size. So, then I [manually] added that [in the final design stage]."*

After determining initial values through calculations, conservative estimates, and intuition informed by knowledge and past experiences, the designer can begin to use the generative design tool to create designs. The exact values of the objectives, parameters, and constraints are often determined through iterative uses of the generative design tool. The tool takes the inputs and generates results that meet the specifications.

4.1.2 Evaluate and Iterate. The designers evaluate results generated by the generative tools in a number of ways. At first, designers can visually evaluate the results to identify the features that appear unexpected or that will not meet specifications. This visual evaluation is based on the designer's knowledge and experience.

"Look at how thin [this feature] is. And sure, you can [make this with a] three axis CNC machine, but [it can't] resist torsion. And so, for every body, there's not just one or two forces that I have to apply. But for every single hole, every single switch, every single mounting point, … I'd have to have loads that go in and go out that would reinforce [the part] to make it not just a twig … And I had to do those individually."

Designers also described analytical methods to evaluate the results. For instance, designers may graph the results to compare the performances of the different designs generated. Additionally, designers can evaluate the performance of the results by running them through analysis software, such as finite element analysis (FEA), to identify areas for improvement.

"Then we could extract the 3D model of this software, put it in FEA, so that we could run some calculations just on the von Mises constraints… we would just take a look at how good or bad [the result was]."

Some of the designers interviewed also mentioned prototyping the results so they can have a first-hand feel for the design.

"How do we decide what the right [design] algorithm is? It's more based on experiences and on prototyping, and also on how comfortable [the design is when] the consumer tries it. Because [it could be] hard [to evaluate], it looks almost the same on the [computer] screen."

Based on the evaluation of the results, designers will iterate on the constraints, parameters, and sometimes the objectives entered in the generative design tool. The adjustments can be based on the designer's experience and understanding of how the constraints and parameters affect the outcome. The iteration of the inputs can also be based on trial and error.

"I was really just experimenting [with] direction of the forces… Sometimes I would get [results] and it would just be a solid block. I don't know what's going on, let's try decreasing some numbers."

Often, designers will also iterate on the constraints and parameters to adjust the aesthetics of the results generated by the design tool.

"We want to show off the new technologies we're incorporating into our product. We wanted something that looks really, really cool, [that] looks like it was made out of generative design. And I spent a lot of time trying to fine tune the parameters to make sure that I got it [to look like that]."

Designers will iterate on the objectives, parameters, and constraints several times. One designer described a total of 37 iterations on their inputs until they were satisfied with the results. The number of trials can be limited by the designer's time and effort required to iterate.

"I found that [with these five results] I have enough designs to draw the conclusion that I wanted to draw from the study in terms of how the shape is affecting the structural performance… I could make the point that I want to do, that you can reach a good set of designs that are … in any case, better than any standard solution from both objectives. And I found that [choosing] five [results] was also [enough] because I was then running a very complex, computationally intensive CFD [computational fluid dynamics] simulation for each of the geometries."

Designers may not fully understand how the generative design tool came up with the final set of designs. Therefore, there is a certain level of trust in the tool and the designer's setup of the design problem that allows the designers to accept the final results.

"I was tweaking these [values in the setup] to just do as good a job as I could. And I trusted at that point that [the design] was fine."

4.1.3 Select. Once the designers have completed iterating the objectives, parameters, and constraints of the design problem, they are left with a set of results generated by the design tool from which they can manually select a design to move forward with. While the results generated are based on optimizing the objectives set at the beginning stage, the criterion for selection is not limited to those performance objectives. Designers will also select a design based on their experience and knowledge to judge which result meets their expectations.

"There's some necking right there that looks kind of suspicious. So, I didn't go with that [result] because it just didn't match my intuition."

Designers can choose a result that better meets a different performance metric not represented in the tool, such as the moment of inertia. Designers may also select lower-performance iterations of the result to improve other characteristics, such as manufacturability.

"I've done that myself in the past where I've made an elective decision that a less efficient [result] is actually going to be easier to manufacture. And I know that just based on personal experience, so that's the one that I'm going to choose to use as opposed to the idealized version of the thing."

Additionally, lower-performance designs can be chosen based on their aesthetics.

"This [design] would have saved us a lot of weight. But it just looks like someone did a bad job at pocketing. And so that was another big thing [and why this different result] is the one that we ended up with… it just looks really cool."

Selection can also be based on other context-specific requirements, such as feature size or acceptance within a specific user group. The designers interviewed emphasized the importance of considering the user at this stage and selecting designs that will satisfy the user's needs.

"We found that it really depends on the location where you're doing this. And that makes it even more important to have this Pareto front or range of designs [to] allow the final user or whoever is going to end up building this [to be] able to choose which geometry is better."

The designer considers all of these factors when selecting from the results created by the generative design tool.

4.1.4 Refine. The final stage of the process is refining the selected design. The level of refinement needed will depend on the specific context, the complexity of the design problem, and how accurately the tool allowed the specific problem to be defined as inputs to the design algorithm. Sometimes, the result from the tool may not need significant refinement and designers will make small edits, such as adding fillets. In other cases, designers may modify significantly. The changes made can be based on the designer's intuition to modify a component that did not meet their standards of design.

"I also was skeptical that these were thick enough, so I made them thicker."

Designers can also modify the design to improve later phases of production, such as manufacturing and assembly, by simplifying and smoothing surfaces.

"This [design] is a lot cleaner and has had some manual intervention. But it is still very much the geometries as produced, but then rebuilt in T splines to be a cleaner object that then gets manufactured out. It doesn't have these kind of weird surface tensions happening and undulations in it. It's just a smoother, more consistent object."

Modifications made to the design can also be based on altering aspects of the design that could not be controlled in the tool setup. For instance, designers described changes made to make the design symmetric to both improve the aesthetics and affect other desired performances.

"I was running FEA on this and… I would remove material from [the center] and add material [to the outside]. So, I was manually adjusting [the design] … Basically I was using generative design as inspiration. I was dissatisfied with the result because it was asymmetric, and it was adding material where I didn't want it. Having weight on the outside is going to add more M.O.I [moment of inertia] and we wanted more weight on the outside [rather than the center] but we couldn't tell [the tool] to do that."

Once all the modifications are made, designers would have finished creating a final design in collaboration with optimization tools through a generative design process.

4.2 Implicit Factors. While all the designers interviewed described the explicit design process, other implicit inputs and outputs to the generative design process were also evident in all of the interviews. The implicit factors in the generative design process are highlighted in gray in Fig. 3.

4.2.1 Designer Expertise. Arguably, the most important input into the generative design process is the expertise the designer brings to influence all the stages of the design process. Designers bring their design experience and knowledge, intuition, and understanding of the users and context to the design process as they define and iterate on the objectives, parameters, and constraints, select from the results generated by the tool, and refine to create the final design. As one designer described, this designer's expertise serves as a foundation that can be built on by the generative design tool.

"I feel in order to master [a generative design tool], you still need to learn traditional CAD software, you still need to have some knowledge and background in engineering and manufacturing processes. Because that [optimization] software is more like another layer, you have to have some foundation first."

In the beginning stages, designers will use their experience and knowledge to establish the relevant objectives, parameters, and constraints to include in the setup. Their expertise is also beneficial in determining the initial values for those inputs, as well as iterating through them.

"This is where… all the past experiences can tell you, or your knowledge on the physics and the behavior of these elements [can] help you to define the variables."

Designers will also select an appropriate design from the results using their expertise to determine which design would work best in terms of various quantitative metrics, as well as other qualitative metrics such as manufacturability and aesthetics. Designers are also the primary input for the users and context specifications in the design process, interpreting those requirements into values and parameters that the tool can understand. It is for these reasons that the tool cannot stand alone without the designer. The tool is meant to augment the engineer throughout the design process, such that the designer's expertise and the tool's computing power can be combined to create a final optimized, high-performing design.

"[The generative design tool] augments what you as an engineer know what works and doesn't work. It expedites you to [your] goal right from the outset."

4.2.2 Qualitative Considerations. While generative design tools mainly allow for quantitative performance-related inputs, many qualitative-related considerations were mentioned by the designers throughout the process. The most evident factor was aesthetics, in which designers found workarounds to influence the aesthetics of the tool outcomes. For instance, sometimes designers would define starting geometries in generative design tools to guide the aesthetics in the design.

"If you apply a starting geometry, that gives you a [designer] defined bounding box. And that can dramatically impact the aesthetics that you get, because [the tool is] trying to bind itself to whatever silhouette that you've created."

Designers and users both value aesthetics in design [40]. The interviews illustrate that while commercially available generative design tools, such as those investigated in the interviews, do not accommodate direct aesthetic input, designers find it an important aspect of design and will find creative workarounds to influence the visual design of the product. There are some design tools that can be used to explore designs based on aesthetics; however, many of these tools are still in the research and development phase and are not widely used [22,41,42].

Designers also described the consideration of factors related to manufacturing and assembly. For instance, one designer mentioned adding constraint geometries in the setup to account for tools used in assembly.

"I'm going to be assembling this, I need to make sure I'm adding clearance for a screwdriver."

These qualitative considerations considered by designers can drastically influence the outcomes of the generative design process.

4.2.3 Exploring and Understanding Design Space. An important implicit output of the generative design process is an understanding of the design space gained by the designer. As designers iterate through the process, they build a better understanding of the design problem and solution space.

"To me it's also a learning experience. I think it helped me gain confidence in what I'm doing and in understanding the problem. When [the tool] gives me the right answer right away, even then, I like to take time to [ask] what's going on? I want to understand it. What happens if you change this or that? So, I think this trial-and-error iteration helps me build a bit of understanding."

In the early stages of iterating on the constraints and parameters, the designers interviewed described a learning curve in which they were able to identify factors they originally did not think to include.

"You can actually see in one of the first studies… I didn't even account for those [forces] yet. And then I was like, oh, wait, we need those somewhere."

This allows for a thorough understanding of all the constraints relevant to the design problem, especially those that traditionally designers would have intuitively included. This learning through iteration also allows designers to identify which constraints are driving the solution space.

"That thickness … we've found, in some cases, that it's driving the whole design decision, because it's what is not allowing the optimizer to go for even lighter structures… so we've seen some cases where one single variable is driving everything."

Since the generative design tool can output several designs that meet the specifications, the generative design process also allows for an understanding of the breadth of the solution space. This understanding of the design space and all the potential solutions can be used by designers as design guidance.

"I was moving things around to like, cut some weight out because basically what I had done was taken the generative design as kind of design guidance"

The understanding of the design space is a unique consequence of the generative design process that cannot easily be gained through traditional design methods.

4.3 Consistency Among Findings. Despite the diverse backgrounds, tools, and applications, all six interviewees described the same process for generative design shown in Fig. 3 and outlined in this section. The main difference between the interviewees was the detail of each step of the process, depending on the product being designed, the context, and the preferences of the designer. For instance, while the need to define an objective at the first stage was mentioned by all designers, they often described different objectives to satisfy depending on the context of the problem. Objectives common to architectural applications include minimizing embodied carbon of structures, maximizing sunlight and airflow. On the other hand, common objectives for aerospace applications involve minimizing weight while maintaining performance. Nevertheless, all the designers described both the overall explicit and implicit stages of the generative design process generated through the interviews.

5 Discussion

A generative design process was derived from interviews with designers who use generative design tools. This comprehensive understanding of the explicit and implicit stages of the design process is useful to begin to understand how the use of generative design tools can affect the process, designer behavior, and design outcomes. The use of generative tools in design has several implications on the design process and how designers approach design. The early stages of defining objectives, parameters, and constraints bring about a constraint-driven design process in which designers focus on the abstraction of the design problem. Designers will iterate through the constraints and parameters to improve both quantitative and qualitative metrics. Learning through iteration allows designers to gain a thorough understanding of the design problem and solution space. This can bring about creative applications of generative design tools in early-stage design to serve as an inspiration and provide guidance for traditionally designed products.

5.1 Constraint-Driven Design. As evident from the interviews, generative design tools require objectives, parameters, and constraints to be defined in the first stages to generate optimal designs. Therefore, designers in generative design focus more on defining the design space and establishing design requirements to generate several designs rather than thinking about the physical design of the product. Additionally, rather than iterating on the physical features of the product, designers modify the inputs to influence the design outcomes. This constraint-driven design results in a different way of thinking as described by the designers.

> *"When you're creating your design, you're thinking about it in a different way. When I'm creating normal parts [through traditional design], I am always applying my intuition- 'I need this beam. And it's gonna connect these two things, and [so I] create the beam first and then I solidify the connection points last. Whereas generative design is a little flip- I only need this little circle here and this point here. It does force me to think more about the constraints and the physics as I'm setting it up. I'm like, well, there's a wall here, so it can't go that way. I need to model that wall."*

Since this constraint-driven design process relies only on the constraints to begin the design process, designers do not need prior ideas for how the product might look. As one designer put it, all the tool requires is an abstraction of the design goal to define the basic inputs to get started in the design.

> *"I have had a few projects where these [parameters and constraints] are not defined very clearly at the beginning. But I think with almost any design project, you're able to understand at the very least the abstraction of your goal, meaning, you know where connection points are, you know where you need certain loads to be constrained, and you know how you might need to access those things, as well as what's going to get in the way. That's all the information that generative design needs."*

This early definition of the constraints and parameters of the design front loads the process such that the product specifications, including the materials and manufacturing methods, can be decided on at the beginning stages. However, as one interviewee mentioned, this constraint-driven design often focuses on the performance aspect and can lead to qualitative-driven metrics to take a lower priority in the design.

> *"And sometimes I feel [that] when you're thinking of optimization and all the technical parts of it, that sometimes it's very easy to lose track of community, [and you create] something that [is] not doable… For example, even this geometry, which is the best performing for [a certain location], I know that this is very hard to build. And every time I've shown this geometry to people [they say] 'umm it looks very, very narrow and I would be scared of [using the product].' In our case, [we are designing] an object that [will] interact with people every day, so it has to be something that you have to be able to evaluate from a design perspective and experiential point of view."*

5.2 Creative Uses in the Generative Design Process. Since the generative design process is constraint driven, the different way of thinking designers must approach the process also leads to a different form of creativity in the process compared to traditional design. Creativity in the generative design process can be found in how designers specify the objectives, parameters, and constraints to influence the final design outcome.

> *"I think it's also creative to say how you define your objective, and that can be super determining in what you end up having."*

Additionally, designers are creative in finding workarounds to overcome the limitations of the optimization tools. For instance, all the designers interviewed described methods they used to influence the aesthetics of the design, from manipulating load cases to making changes during refinement.

> *"As you become more and more familiar with generative design as a technology, you're able to start to predict what kind of geometries you're going to get out. And these can be manipulated by clever load case usage and the way that you might insert obstacle [geometries]."*

Designers can also find creative ways to use the generative design tool as part of the design process. While generative design tools can be seen as a means to generate a final outcome, the generative design process can also be used to learn about the design space, to generate initial designs as inspiration, and to explore the breadth of design solutions.

> *"Then from that [result stage], we would actually end the process with something that we thought was okay in terms of FEA and geometry. And we would actually then stop using the [generative design tool] and make a new part from scratch based on this [result]."*

Other designers maximize what they can learn from the generative design process. For example, some of the designers interviewed described instances in the early stages of design in which they only defined the preserved and obstacle geometries, while excluding any loading constraints. This allowed them to use the tool to generate unconstrained designs to illustrate all the potential ways the geometries can be connected, allowing designers to explore the breadth of the design space.

> *"When I do design work myself, if I have engineering requirements defined at the beginning, the very first exercise that I will do is setting up a study in generative design and looking at what the unconstrained geometry produces. And that gives me a very quick visual indication of how I might want to design a traditional object, or how I might refine what I'm doing to produce a generatively designed output."*

Designers can also find creative uses of the generative design tools. Some designers look to use these generative design tools to create parts with a certain visual design, leaning into the tool's aesthetics to create organic, generatively designed looking parts.

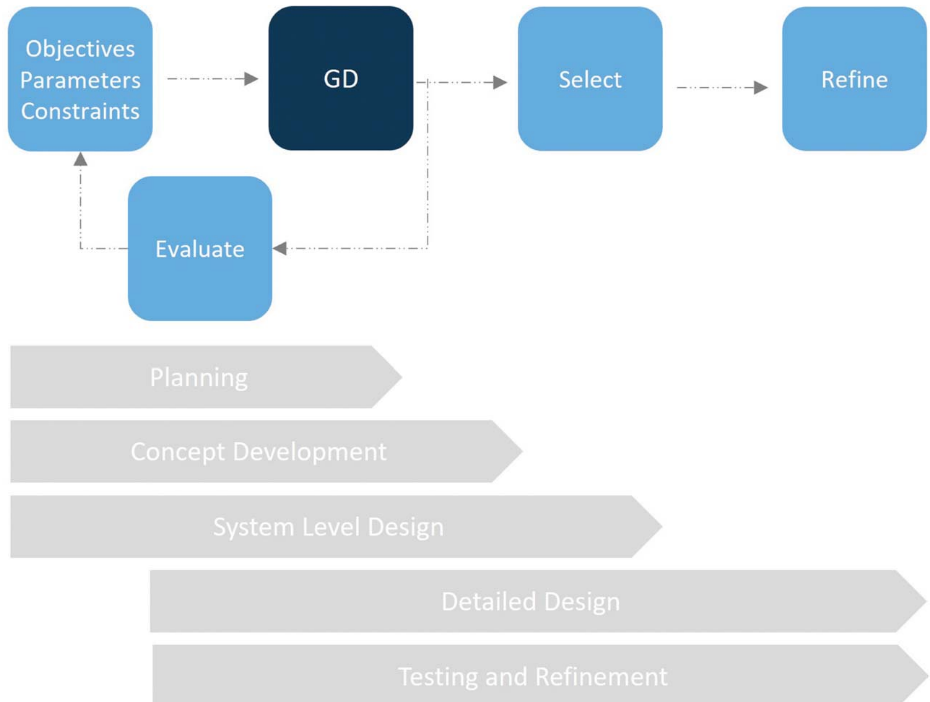

Fig. 4 Overlap of generative design (GD) process (top) and a more traditional design process (bottom, adapted from Ulrich et al.). The generative design process allows for traditional design stages to be carried out in parallel.

> *"I took one of these [generatively created results] out, I cut it in half and mirrored it to ensure that it was symmetric. And then I brought the result into generative design as the starting geometry to accentuate and exaggerate the features… But the original version of this [design], that the generative design produced [without a starting geometry was] not as complex as this. It was a lot simpler with just a few cross brackets in place to support the elements that it would produce. But by taking that and bringing it into generative design as a starting geometry, it ended up creating something geometrically more complex, and something that I really didn't just like the aesthetic of, it felt right to produce that version of it."*

These creative processes in the design setup and iteration of the design problem as well as the tool application to explore the solution space are different from traditional design processes. Therefore, methods to encourage creative events in traditional design processes may not be applicable in generative design and new techniques may need to be developed [41]. Additionally, there is a general understanding that the design process affects the design outcome. Therefore, it is possible that these creative uses of the generative design tool can also lead to creative design outcomes. The creativity of the design outcomes was not measured in this study and should be investigated further.

5.3 Early-Stage Design. It is evident from the interviews that generative design is impactful in the early stages of the process. While designers may not have a thorough set of parameters and constraints at the beginning of the process, iterating through the designs can allow them to learn what all the constraints are and which, if any, are driving the design solutions.

> *"…[you] start evaluating the results, and you're seeing maybe [you] should narrow this bound, or you see that all the variables are towards the limit of a certain bound, you can tell that you should expand it a little more and allow it to explore. So, I would say there's some evaluation [and] there is also reevaluating the bounds while you're doing the optimization."*

Designers can also study the outcomes of the generative design process to gain insight into the influence of the parameters and constraints on the physical design. The geometries produced can illustrate how the loading constraints influence the aesthetics of the design.

> *"I get a sense of geometric considerations that are gonna impact the aesthetics. I can see here that I've got some dominant lines, there's clearly a lot of load being transferred in here and I have some sub dominant lines that are helping reinforce what's happening. That helps me understand what my design constraints might be."*

The outcomes of the generative design process can also elucidate designs in the solution space that the designer did not consider or are contrary to their initial intuition.

> *"This is an interesting take away because initially, I drew the geometry for this [shape in a certain] way, and I'm thinking that from a [thermal] radiation point of view it makes sense … But then I found out that many of the optimal surfaces [generated by the tool] are actually in reverse. And the reason for that is that this [obstacle geometry] is really driving the structural performance. So [the design] really wants to get thin, but it can't because of this constraint, and that's more important than the radiation part of it. So I think it's very interesting to have your own understanding of things but then the [designs generated] are different."*

The understanding gained from the generative design process can be used to inform designs created through a traditional design process. For example, one designer used the generative design tool to produce a design which they used as inspiration to design the product through traditional means.

> *"Here's the pure generatively designed [product]. This is with no manufacturing consideration so it's pure geometry. And then this is how I might build [three] different versions of the same product by hand in traditional CAD, based on what this [generative result] is telling me. [First] rebuilding it as a T splines object that's more organic, and very reminiscent of what the generative design part was. Rebuilding [it again] as a solid model part that I would then cast. And then a third iteration as a consideration for manufacturing with sheet metal. So, these are all getting further and further departed from what generative design produced."*

Generative design can be beneficial in early-stage design to gain a deeper understanding of the objectives, parameters, and constraints affecting the design. This understanding can be used to inform designers of the problem and solution space and can even be used as inspiration for designs created through traditional means.

The example of creative processes provided from the interviews illustrates that the generative design process can be used not only to create a final design outcome but also as a tool within traditional design to inform various stages including planning, concept development, system and detailed design, testing, and refinement, as shown in Fig. 4 [42]. Generative design can be used in the early planning stages to understand the problem space by learning what are the parameters and constraints, which constraints drive the design, and how they can affect the design geometry. It can also be used to make detailed level design decisions earlier on, such as manufacturing method and material selection. Generative design tools can also be used to create designs that explore the concepts found in the breadth of the solution space. These designs can either be used as inspiration for initial concepts to be further developed through traditional design or they can continue to be expanded on through testing and refinement in computational tools to generate a final design.

6 Conclusions and Future Work

A generative design process provides the opportunity for designers and AI driven optimization tools to interact in design to generate high-performing products. Using generative tools in design affects the design process, designer behavior, and design outcomes, as illustrated through six interviews conducted with designers using generative design tools. The findings from this study address the research questions as follows:

> *RQ1: How does the use of generative design tools in product design impact the design process?*

Designers will consider several factors throughout the generative design process. Quantitative performance metrics, such as weight, are considered in defining and iterating the objectives, parameters, and constraints. Designers will also define qualitative metrics, such as aesthetics. The generative design process also allows for the determination of manufacturing and assembly constraints earlier on in the process. These factors are considered through various methods. Designers can use quick calculations or various analysis methods to determine the values of the objectives, parameters, and constraints. Designers will also use their intuition, past experiences, and knowledge to define, evaluate, and iterate on the design. Prototypes can also be useful to obtain a hands-on feel of the design and determine appropriate changes. These various factors and methods used by the designers in the generative design process are summarized in Table 2.

> *RQ2: How does the use of generative design tools affect designer behavior and approach to the design process?*

Table 2 Factors considered by designers in various stages throughout the generative design process and the methods designers use to include these factors

Factors
• Quantitative Considerations
• Qualitative Considerations (Aesthetics, Uses, and Context)
• Manufacturing and Assembly
Methods
• Designer Expertise (Intuition, Knowledge, Experience, Visual Judgment)
• Analysis and Calculations
• Prototyping

There are many implications of the generative design process and its effect on a designer's approach to the design process. Designers begin the process by using their expertise to specify the objectives, parameters, and constraints associated with the design problem. Designers will then iterate through the inputs, learning more about the design problem space along the way. Designers select and refine the results, often incorporating other important qualitative-related specifications such as user preferences. This constraint-driven design process forces designers to think about the design problem differently and to approach the design problem with an abstraction of the design problem rather than an idea of the physical design of the product. Designers are creative in defining the parameters and constraints to influence the process outcomes. Designers can also be creative in their uses of the generative design process to explore the design problem and design solutions and to provide inspiration in the early stages of design.

There are some limitations in this study that can be addressed with additional work. The findings in this study may be constrained due to the small sample size of interviewees. The limited sample size did not allow for deep exploration of the subtle differences in the process that may exist between different generative design tools or between fields of design. Future work can include more interviews to explore the breadth of tools and the depths of each stage in the process and the design outcomes.

The findings from this study provide insight into the implications the use of generative design tools in design can bring to the design process. Controlled lab experiments can be used to understand the implications of the process and its effect on the designers and design outcomes. For instance, it was observed that designers used the generative design tool to learn more about the parameters and constraints driving the solution space. Future experimentation can be used to determine how this learning through iteration can be helpful in the design and how it can be formalized such that it can be used to its fullest potential. The interviews also uncovered many limitations in the commercially available generative design tools that required designers to find their own workarounds to represent their design problem as inputs to the tool. For example, to influence the aesthetics designers may alter the loading forces, change the geometry constraints, and modify the safety factor. It is unclear what effect those different workarounds may have on the performance of the design outcome.

The detailed generative design process derived in this study illustrates the diverse uses of generative tools in design and the implications these uses have on the design process. Through this understanding, the effects of the interactions between human designers and generative design tools on behaviors, design structure, and overall outcomes should be further explored. The findings from this research can be used to further define and refine collaborative design with human designers and generative design tools in the design process.

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Conflict of Interest

There are no conflicts of interest.

Data Availability Statement

The data sets generated and supporting the findings of this article are obtainable from the corresponding author upon reasonable request.

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