Generative Design Tools: Implications on Design Process, Designer Behavior, and Design Outcomes

by

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Abstract

Generative design tools, empowered by recent advancements in computational algorithms, 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. Much of the research focuses on the technical development and application of these tools, while less attention has been paid to how generative design tools are used from the designer's perspective. Three main contributions of this dissertation include a development of a generative design process, observations of the implications of the use of generative design tools, and an understanding of how designers balance multiple objectives throughout a generative design process.

A grounded theory approach based on the experiences of designers was first used to develop a generative design process. Six in-depth interviews were conducted with experienced designers from different disciplines who use commercial generative design tools in their work, detailing the design processes they followed. A qualitative-based coding and analysis of the interviews was used to generate 161 coded themes describing the design process. Through these themes, a provisional process diagram for generative design and its uses in the early-stage design process is proposed to outline explicit and implicit stages of the design process.

Several implications of the use of generative design tools on the design process and designer behavior were developed through additional analysis of the interviews. 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, such as engineering performance and product styling. This 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.

It was observed that generative design tools primarily allow for quantitative inputs to the tool while qualitative metrics, in particular aesthetics, are considered indirectly by designers. To explore this further, controlled lab experiments were conducted to understand how designers balance quantitative and qualitative objectives while using generative design tools. Thirty-four participants completed two design tasks (with and without generative design tools) with the same qualitative and quantitative objectives. Counterintuitively, designs created in the task without generative design tools had a statistically higher quantitative performance than those created with generative design tools. On the other hand, the designs produced with generative design tools displayed a greater aesthetic diversity and expanded a larger portion of the objective space. Participants also expressed the ability to focus on the qualitative objectives by delegating the quantitative objective to the generative design tool. This showcases the potential for generative design tools to assist in the design process and leveraging the expertise of both the human designer and the generative design tool to allow for greater consideration of various objectives throughout the design process.

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Chapter 1

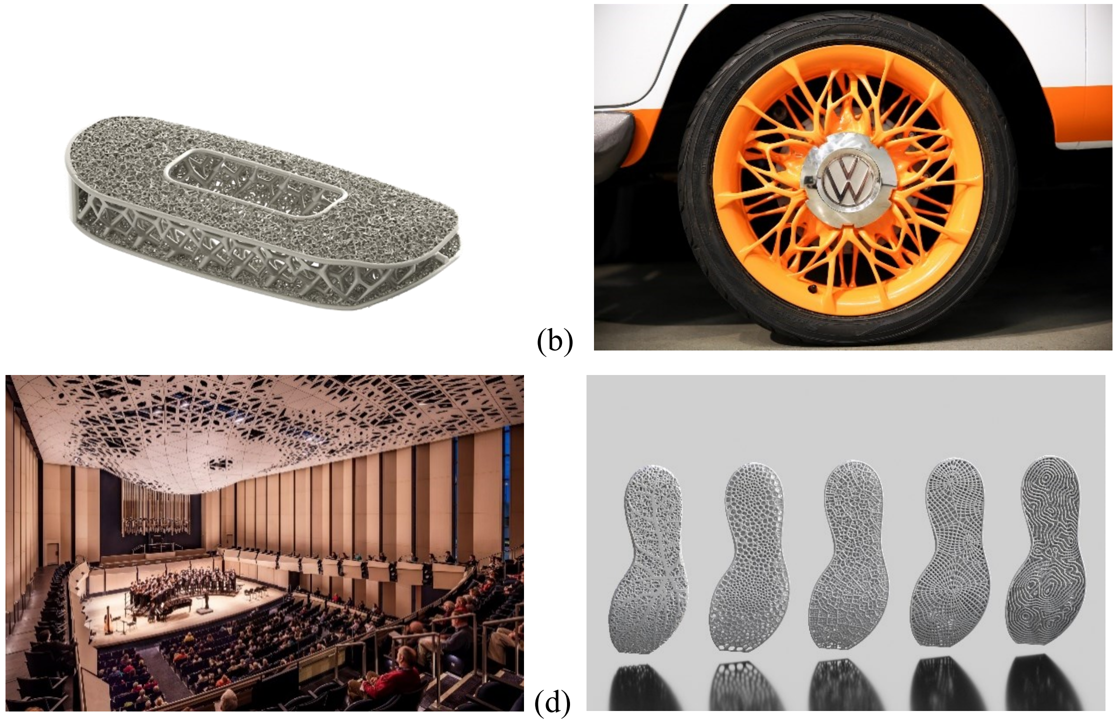
Introduction

1.1 Motivation

New developments in generative algorithms offer designers new tools that can be integrated into the design process to potentially improve the outcomes and allow for greater consideration of design requirements [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 other concept generation [4,5] to later stages of design evaluation [6,7], prototyping [8] and production [9]. Generative design tools, as they stand now, do not replace the designer, but rather are tools that can augment the human designer's abilities. This collaboration between designer and generative tool throughout the design process introduces opportunities for approaches which vastly open up the space of possible designs beyond what human designers alone can generate.

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. These generative design tools can be custom built tools specifically made for a certain research task or industry. Some commercially available generative design tools with more general applications have emerged over the past decade and are increasing in use, such as NTop and CATIA generative design tools. Many of these tools also lie in industry and research communities in which custom tools are built within companies to achieve a specific task or in research spaces to expand the functionality and applications of these tools. While these tools were originally used to evaluate and optimize products in the later stages of design, the latest wave of computation tools have 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].

There are many examples in both research and industry where generative design tools were vital in generating high-performing products. These generative design tools have also allowed designers to optimize for many different objectives. Examples of products optimized for various objectives are shown in Figure 1-1. These include a spine implant optimized for strain while maintaining appropriate bone structure and density [15], a tire hub optimized for stress while also taking into consideration aesthetics [16], a ceiling for a music building optimized for acoustics and lighting [17], and a shoe insole optimized to give additional support at pressure points [18]. These products created using generative design tools showcase the potential of these tools to create high performing, complex, and custom designs through a design process that involves both the human designers and generative design tools.



(a) (b) (c) (d)

Figure 1-1 Examples of products created using generative design tools. (a) NuVasive spine implant (b) Volkswagen and Autodesk tire hub (c) Voxman Music Building (c) New Balance and Nervous Systems shoe insole

At the same time, design problems are very complex and often encompass more objectives than can be represented in the generative design tool. For instance, an architect may want to design a building that minimizes carbon emissions while incorporating their signature style. As such, the designer must also understand how the tool can be best incorporated in their process. The perspective taken in this dissertation is that the ideal collaboration between designer and generative design tool is one in which the expertise of both is utilized in the process.

Traditional research on generative design tools involves advancing the tool itself and the algorithm supporting the tool or exploring its potential uses and products that can be created. However, more work is needed to understand how they are used by designers and how their use can affect the design process and design outcomes [19]. This need motivates the following overarching question:

How are generative design tools used by designers and what are the implications of their use on the design process, designer behavior, and design outcomes?

While enhancing the advances of generative design tools with the expertise of the designer can allow for higher performing and complex products to be created, designers must approach the design process differently to incorporate these tools into the process. The overall goal of this dissertation is to outline how generative design tools are used from the designers' perspectives and to recognize the implications of their use. Through this we can understand how generative design tools can be appropriately learned and used in the design process to augment the designers' expertise and open new possibilities of high performing design outcomes. The overall research question is broken down into several questions investigated through this dissertation. Chapter 2 focuses on understanding the generative design process through the question, *how does the use of generative design tools in product design impact the design process?* Chapter 3 investigates the implications of generative design tools through the question, *how does the use of generative design tools affect designer behavior and approach to the design process?* Chapter 4 delves deeper into designers' interactions with generative design tools through two questions: *how do designers balance qualitative and quantitative objectives while using generative design tools?* and *how are qualitative and quantitative objective performances affected with the use of generative design tools?*

1.2 Background

1.2.1 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. These tools use designer specified inputs to algorithmically generate a large number of design outputs for designers to explore in a relatively short period of time.

Inputs defined by designers The inputs defined by the designer depend both on the goal of the designer for using the generative design tool and the types of inputs the tool can process. A common use of generative design tools is to optimize the design of products according to certain design objectives. In these cases, designers will specify the objective goals and the relevant design constraints in the tool. Another use of generative design tools is to explore the possibility of designs in the design space [20]. This requires certain design parameters and constraints to be defined. The types of inputs that can be accommodated also vary between tools. For instance, some tools allow for manufacturing processes to be defined while others do not. Some tools allow designers to define limited objectives such as weight or stress, while others can incorporate many varying objective functions.

Generative algorithms The generative algorithm uses the designer specified inputs to rapidly generate and evaluate hundreds or even thousands of designs. The types of generative design algorithms differ between tools. These can include, but are not limited to, genetic algorithms (such as Non-Dominated Sorting Genetic Algorithms, NSGA-II) [21] and deep generative models (such as Generative Adversarial Networks, GANs) [22]. In some cases, such as with commercially available generative design tools, the algorithm behind the tool is often unknown and cannot be altered by the designer. As such, the generative design tool is seen as a black box by the designer and through time they learn to manipulate the outputs by controlling the inputs given to the tool.

Outputs of generative design tool The outputs of the generative design tools rely both on the inputs given by the designer and the type of algorithm used. The algorithm defines the criteria for acceptable designs, which can include meeting the design objectives, parameters, and constraints and ensuring diversity of the designs presented. Generally, the tool outputs hundreds of designs within a short period of time that follows the criteria of the algorithm and fulfills the inputs defined by the designer.

Much of the research on generative design tools aims to advance the algorithms or explore the applications of the outputs of the generative tools. This dissertation focuses on the human designers' perspective and influence on generative design tools. The diversity of generative design tools and the constrained access to many of these tools limits the generalizability of findings from studying a subset of generative design tools to all tools. While we believe the findings from this study are applicable to many other generative design tools that embody the characteristics defined above, we do recognize that the conclusions are not appropriate to all generative design tools. As such, it is important to understand the types of tools used in this study and the context in which they were applied. The first two chapters of this work use commercially available generative design tools used in both research and industry to establish a generative design process. Then a generative design tool that uses an NSGA-II algorithm to generate optimal and diverse designs is used to investigate how designers balance different objectives while using generative design tools. These tools and contexts are described in more detail in the respective chapters.

1.2.2 Tools in Generative Design

Generative design tools vary widely in application, from improving quantitative performance, to increasing design diversity and creativity, and inspiring designers in the early stages of design. For instance, General Motors used Fusion 360 Generative design to redesign seat brackets. 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 3-D printed part as shown in Figure 1-2 [23].

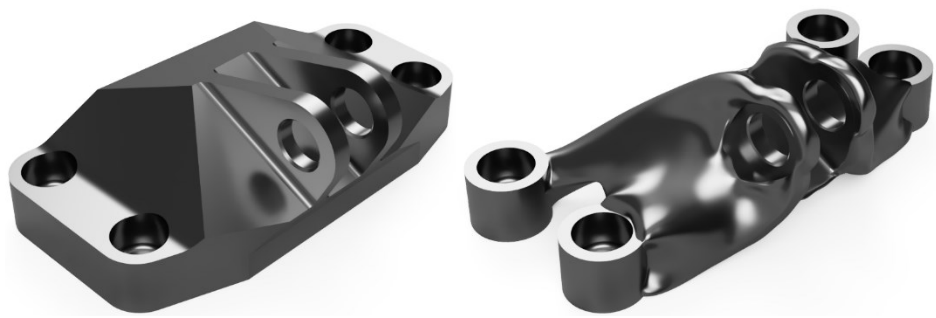


Figure 1-2 Comparison of the original GE bracket (right) with an optimized bracket (left) created using Autodesk Fusion 360 generative design.

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 [14]. 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 influence the product design process changes to integrate these tools effectively in design.

1.3 Thesis Organization

There are five chapters in this dissertation. Chapter 2 uses interviews of designers incorporating generative design tools to develop a generative design process. Chapter 3 builds on these interviews to establish observations on the implications of using these tools on the design process and designer behaviors. Chapter 4 further investigates one of these implications through an in-lab experiment to understand how designers balance quantitative and qualitative objects while using generative design tools. Chapter 5 concludes this dissertation with its contributions and suggests areas of future research.

Chapter 2

The Generative Design Process Derived from Designers

2.1 Introduction

The use of generative design tools provides a computational dimension to the design process, enabling the broader exploration of the design space and the generation of higher performing designs while potentially altering traditional design stages. To harness these benefits of using generative design tools, an understanding of how designers interact with the tools throughout the design process needs to be developed. Generative design tools still require some level of expertise of human designers to set up and engage with the tool throughout the design process. Thus, the generative design process that outlines the distribution of roles between human designer and generative design tool needs to be understood such that the expertise of both collaborators can be integrated to foster innovative and optimized design outcomes. This chapter and the next use interviews of designers designing with commercially available generative design tools to develop a generative design process and understand the implications of using generative design tools on designer behavior and design outcomes.

A grounded theory approach was used to develop a generative design process rooted in the experiences of designers. The findings aim to provide key insights about the interactions between human designers and generative design tools within the design process by addressing the following question:

How does the use of generative design tools in product design impact the design process?

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. The findings in this section are also published in Saadi, et al. [27].

2.2 Related Work

2.2.1 Traditional Design Process

The traditional design process in which designers go from identifying a design problem to creating a commercially ready product, such as the one illustrated in Figure 2-1, has long been established in the literature [28]. The designer-driven process focuses on the shape and architecture of the product or service being created and relies on the designer to ensure optimal functionality, usability, and aesthetic design.

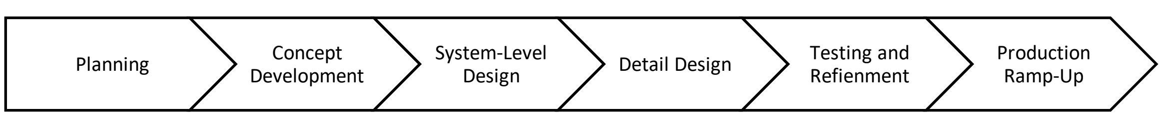


Figure 2-1 The product design process from Ulrich, et. al., (2019)

The incorporation of generative design tools has the potential to disrupt this design process as the tools take on some of these roles. 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 [24]. 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 of inputting into computational tools.

2.2.2 Generative Design Process

Generative design tools in the design process can take on many forms with varying levels of involvement from the generative design tool as shown in Figure 2-2 [29]. 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 [30]. 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.

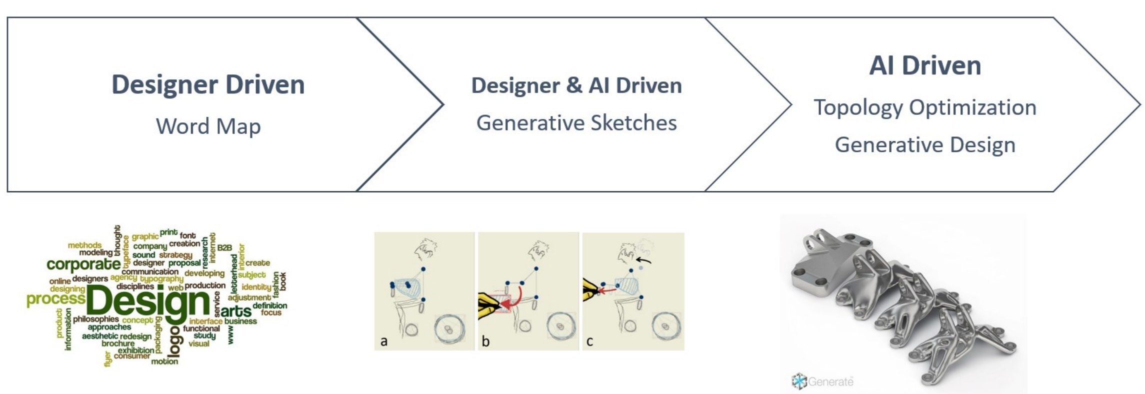


Figure 2-2 The varying levels of generative design inclusion

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 understanding the generative design process in which the generative tool takes on a larger function.

No one consistent process for how designers should design using generative design tools has been outlined in detail in previous literature. Some design processes have been suggested in prior research or by companies that create generative design tools, such as the one shown in Figure 2-3 [31,32]. However, these processes focus on the tools' role in the process and the role of the designer in the process is overly simplified. The study described in this chapter 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.

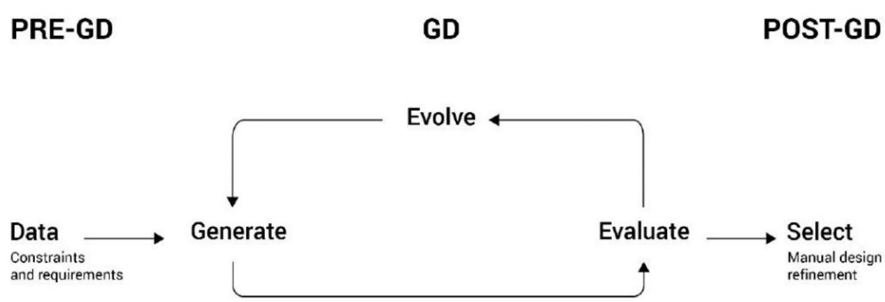


Figure 2-3 A suggested Generative Design Process [32]. These processes focus on the tool and simplify the role of the designer.

2.3 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]. Contrary to other research methods, the grounded theory approach does not begin with a hypothesis. Rather, the process starts with data collection through qualitative methods such as interviews and field observations. The collected information is analyzed early on through a systematic approach to develop theories, which are further iterated and refined throughout the data collection process. 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.

2.3.1 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 (for example 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. The interviews began by asking the designer to walk through their process to create a specific product created using a generative design tool. Subsequent questions were based on were dependent on the interviewees responses to further understand their process and reasoning for certain decisions (some examples included in Appendix A). 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.

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)

Audio recordings of the interviews 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). 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 of the overall process was gained from additional interviews [37].

2.4 Results

The design stages generated through the analysis of the interviews were used to outline the generative design process as described by all the interviewees. The quotations 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.

The generative process that emerged from the interviews is shown in Figure 2-4. In the first stages, 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 Figure 2-4. 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 chapter.

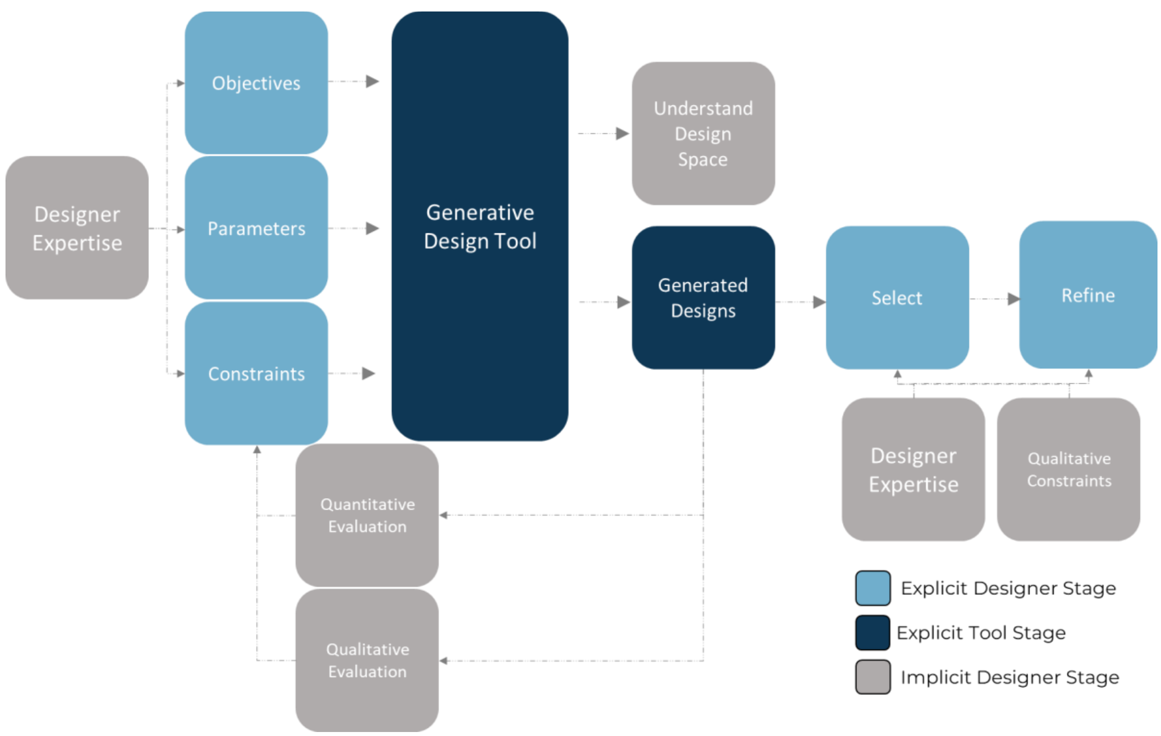


Figure 2-4 The generative design process derived from the design processes described by the interviewed designers.

2.4.1 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 optimize the design. The interviews indicate that the objectives that designers specify in the optimization tool relate to performance metrics, such as minimizing weight or maximizing stiffness. Some projects may require a different objective such as maximizing thermal efficiency to design a heat sink or minimizing the embodied carbon to account for the environmental footprint of a building. 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, for optimization. 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."*

While the precise values of the constraints are not well always 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, 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 throughout 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 and experts and the 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 in at later stages.

> *"But 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, knowledge and past experiences, and intuition, the designer can begin to use the generative design tool. 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.

2.4.2 Evaluate and Iterate

The designers evaluated results generated by tools in a number of ways. At the first level 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 on the inputs can also be based on trial and error.

"I was really just experimenting [with] direction of the forces…Sometimes I would get a study 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 set up 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."

2.4.3 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 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 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.

2.4.4 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 set up. For instance, designers described changes made to make the design symmetric to both improve the aesthetics and to 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.

2.5 Discussion

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 design process are highlighted in gray in figure 3.

2.5.1 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 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 set up. 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 tools 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."*

2.5.2 Qualitative Considerations

While computational 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 [38]. 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 [25,39,40].

Designers also described the consideration of factors related to manufacturing and assembly. For instance, one designer mentioned adding constrained 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.

2.5.3 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 iteration 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. 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 be gained through traditional design methods.

2.5.4 Consistency Among Findings

Despite the diverse backgrounds, tools, and applications, all six interviewees described the same process for generative design shown in figure 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 unique 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.

2.6 Conclusion

A generative design process provides the opportunity for designers and generative tools to interact in design to create high performing products. Using generative tools in design affects the design process, designer behavior, and design outcomes, as illustrated through six interviews conducted of designers using generative design tools. The findings from this study address the following research question:

How does the use of generative design tools in product design impact the design process?

In the generative design process, designers define the objectives, parameters, and constraints to give to the generative design tool. Based on these inputs, the tool will generate outputs which are then evaluated by the designer. The designer will modify the tool inputs until they are satisfied with the results generated by the tool. Designers will then select from the designs and modify the designs to meet all the design requirements. Throughout this process, designers will consider several factors. 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.

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, & Context) • Manufacturing and Assembly
Methods
• Designer Expertise (Intuition, Knowledge, Experience, Visual Judgement) • Analysis & Calculations • Prototyping

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 use of generative design tools in design and the advantages it 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 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 effects these uses have on the design process. Through this understanding the impacts of the interactions between human designer and generative 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.

Chapter 3

Observations on the Implications of Generative Design Tools

3.1 Introduction

The previous chapter established a generative design process based on the actual practices of design engineers. Explicit stages by the designer and the tool and implicit inputs and outputs of the process were outlined. The generative design process uncovered through the interviews of six designers using generative design tools showcases that there is a different distribution of roles between human designers and the design tools, requiring designers to approach the design process with a different way of thinking. This chapter delves deeper into the interviews conducted to understand the implication of using the generative design tools on designer behavior and design outcomes through the following question:

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 [41–43]. 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 decision, which differs between designers, can result in different design outcomes between designers to common design objectives [44]. The findings in this chapter are also published in [27,45].

3.2 Related Work

3.2.1 Effect of Design Tools

Computational tools in design can influence the designer's cognitive processes, their design exploration, and overall designs generated [41]. 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 set up [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 [46]. 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 [47]. The emotions of human collaborators while using computer aided design software may also be affected in human design teams [48]. Similarly, the interaction between human designers and artificial intelligent tools, such as 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 to 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 [49]. Zhang et al. examined the impact of abrupt problem changes on AI-assisted design teams [42]. They found that the AI tool improves 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 of designers understanding 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 [50]. 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 [43]. In-lab experiments with novice designers indicated that computational tools affect both how designers interact with the tool and the overall design outcome. Chaudhari et al. 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 [51].

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 [50]. 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 tool and human designers throughout the process.

3.3 Methods

The results in this chapter build additional analysis on the interviews introduced in chapter 2. Qualitative research methods were used to analyze the semi-structured interviews for emerging themes on the implications of using generative design tools on the designers' behaviors and design outcomes.

3.3.1 Transcription & Coding

Audio recordings of the interviews 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 [52]. The first level of coding utilized descriptive open coding, in which the data was segmented into preliminary categories that summarized the topic of the data passage with a focus on the meaning of each statement [37,53]. 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 [53]. For instance, using "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 [53,54]. The two subcategories of "Setup method: intuition" and "Setup method: context" were grouped under the theme of "Constraints" developed in the theoretical level of coding. An example of this coding process is shown in Figure 3-1. 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 [36,52]. Additionally, study participants, design tool experts, and qualitative research methods specialists were consulted throughout the coding process to validate the findings through the analysis [53].

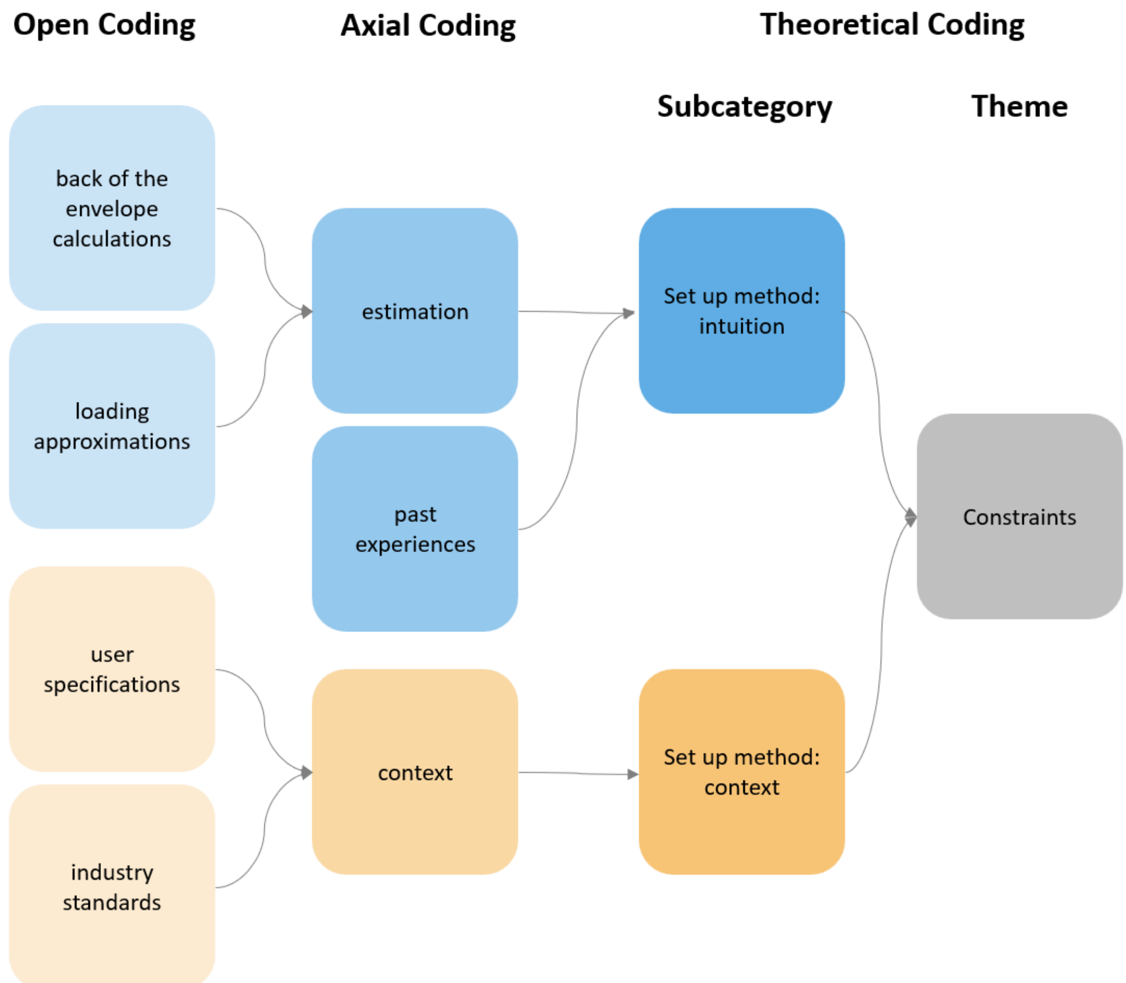


Figure 3-1 The three stages of coding used: open coding, axial coding, and theoretical coding. Examples of coded categories from the data under the theme of "Constraints" are shown.

3.4 Results

A generative design process was derived from interviews of designers who use generative design tools as outlined in Chapter 2. This comprehensive understanding of the explicit and implicit stages and outcomes 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. 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 serve as inspiration and provide guidance for traditionally designed products. The implications of the process derived through a qualitative analysis of the interviews are detailed in this section.

3.4.1 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 [traditionally], 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 it 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] looking at 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."*

3.4.2 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 and 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.

> *"What I did was, 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 set up 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 [55]. 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.

3.4.3 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 on the influence of the parameters and constraints on the physical design. The geometry 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.

3.4.4 Qualitative Metrics

Since computational design tools are constraint driven, the inputs to the design problem are related to measurable performance and typically there are no direct methods to input qualitative constraints such as aesthetics. However, all the designers interviewed mentioned some aesthetic considerations in their designs, whether it be through defining the parameters and constraints or in the final refinement.

> *"I was closely working with one of the mechanical experts in the department and we are very inclined to aesthetics. So, we would always play [with the parameters] a little bit to make it more beautiful, in a range where it wouldn't change the constraints and would allow us to play in this safe zone."*

Similarly, the performance of the outcome can be prioritized by managers, clients, and users. However, as one designer observed, the aesthetics of the final design is also subconsciously considered by the other stakeholders.

> *"What is funny is that in the [design] reviews, in these mechanical regions aesthetics is never something you talk about. And you actually don't want to talk about that. But when you are on site with the people installing the [product], and then the client comes to see the [product], then it becomes something that they are sensitive to. When [the design] is on the screen they don't really say anything. But when it's installed and it's shiny, and you see [the product in person], that is when the manufacturer and your [client] will have the feeling that it looks good. Often, we would have this feedback of 'You'll make anything look so good compared to what we had before.'"*

The aesthetics of the design is not limited to how beautiful the design may look. It can also be linked to the design's performance and whether the product looks like it will function to specification.

> *"We were so often looking for something that looks robust. And sometimes just having sharp edges helps you make it a bit fatter, a bit more square, and that helps the piece looks more resistant, even if it's not."*

Often designers using these generative design tools are drawn to the aesthetics generated by the tool. Some designers look to use these tools to generate parts with a certain visual design, leaning into the tool's aesthetics to create natural, generatively designed looking parts.

> *"What I did was, I took one of these [computationally generated 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."

On the other hand, there may also be cases where the aesthetics of the computationally designed product is not important. For example, if the part generated will not be seen in the final product, then the aesthetics does not matter, and the performance of the outcome is the main consideration of the process.

"With the design team and iterations, they're able to really refine the [design] down and [it] still is visually noisy, and from a purely aesthetic perspective may not necessarily be something that someone wants to use, but this is shrouded in a covering anyway, so it doesn't make a huge difference."

Designers and users both value aesthetics in design [38]. The interviews illustrate that while many of the computational tools 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 [25,39,40].

3.4.5 Influence of the Designer's Own Expertise

Designers input their own expertise throughout the stages of the generative design process. Designers use their experience to set up the objectives, constraints, and parameters. They will also evaluate the results based on their intuition and knowledge. Designers will iterate on the tool inputs to impact the quantitative and qualitative metrics of the outcome, such as the aesthetics. All these influences of the designer can be subjective and can differ between designers [44]. As such, designers can create very different designs based on the same design problem.

> *"While aesthetics is a very subjective experience, you are still able to manipulate and control it… Even if you don't use the final geometry, you've got a very clear sense of what an optimized version will look like and use that as the jumping off point to create something manually."*

3.4.6 Novice and Expert Designers

The level of experience of the designers interviewed varied between several months and years. It was observed through the interviews that the approaches and uses of the tools differed between experts and novice users of computational tools. Experienced computational designers used the tool more creatively. They used the tool in the early stages of design to learn the problem space and solution space. They intentionally controlled the aesthetics through clever set ups. Expert designers would also use the computational tool to generate outcomes that can be used as inspiration for manually designed products. They can also predict the outcomes of the tool based on the input constraints and parameters and whether the outcome of the tool will work in reality.

> *"[Expert] designers, use [generative tools] to design. They know what will happen. They know [if] this structure will work out or won't work out… It looks great on the [computer] screen, but when you [test its performance], it is super fragile or super hard. So, I feel like they have the experience so they can make the call."*

Despite the observed differences between novice and expert designers using computational tools, the high-level generative design process described by each designer was consistent, from the tool set up and iteration, to the design selection and refinement. This indicates that generative design tools require designers to undertake a specific process for the tool to be used. Even novice designers that use the generative design tools for the first time can generate results if they can approach the tool with an abstraction of the design goals, constraints, and parameters. This raises the question of whether computational tools can flatten the curve between novice and expert designers such that products that satisfy design specifications can be created despite the designer's level of experience.

3.4.7 Process Flexibility

The flexibility of the generative design process also differs from that of the traditional design process. As one designer put it, in traditional design it can be difficult to absorb changes to the design requirements, especially in the later stages of design.

> *"It's just frustrating, because then you have to go back way further [in the design process]. Sometimes, you know the routine you have to follow to make that happen, but you just don't want to waste time."*

On the other hand, since generative design tools only require inputs for the objectives, parameters and constraints, designers can be more flexible in the early stages of design. As designers are not manually generating the physical product, it becomes easier to computationally create different designs by simply changing and iterating on the parameters and constraints. This can save time in the design process and allow for more changes when the constraints are not mature.

> *"Once the [tool] was set up, you can always in the beginning play around… And that was basically the idea, to be able in the first phase, at least setup everything so that when you have an input that is a little bit more frozen, you can just push a button and have a geometry that that is corresponding to it."*

There can be some downsides regarding the flexibility of the final product created using generative design. Traditionally, designers will try to build flexibility in the design by making it more modular, such that they can accommodate changes in the design specifications later on [28]. The modular designs created can more easily be used for future variations of the design [56]. However, since the generative design has more flexibility built into the process, it is possible that the designs generated cannot easily be used or adapted in future design problems to satisfy similar yet slightly different design specifications.

3.4.8 Design Time

Using generative design tools has the potential to change the amount of time spent in each stage of the design process and possibly reduce the design time as described by some interviewees. The generative design tool creates design solution within hours. It also allows some of the design to be front loaded, determining the materials and manufacturing processes earlier on as inputs to the tool.

> *"You can take something that would typically take you a really, really long time and not only reduce the lead time, but you can front load it."*

However, there may be cases where the design problem cannot be accurately represented in the generative design tool. This can be due to the complexity of the design problem, with multiple performance and qualitative objectives to optimize for. It can also be due to limitations in the generative design tool. Therefore, there may be significant revisions that need to be made to the design after using the generative design tool. In these cases, the time spent defining and iterating the design problem and modifying the designs may end up negating any time saved generating designs using the tool.

3.5 Discussion

Many implications of the use of generative design tools were observed though a qualitative analysis of interviews of designers using generative design tools to address the question:

How does the use of generative design tools affect designer behavior and 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 will then 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 use of the generative design process to explore the design problem and design solutions and to provide inspiration in the early stages of design.

The example of creative processes provided from the interviews illustrate 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 Figure 3-2 [28]. 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.

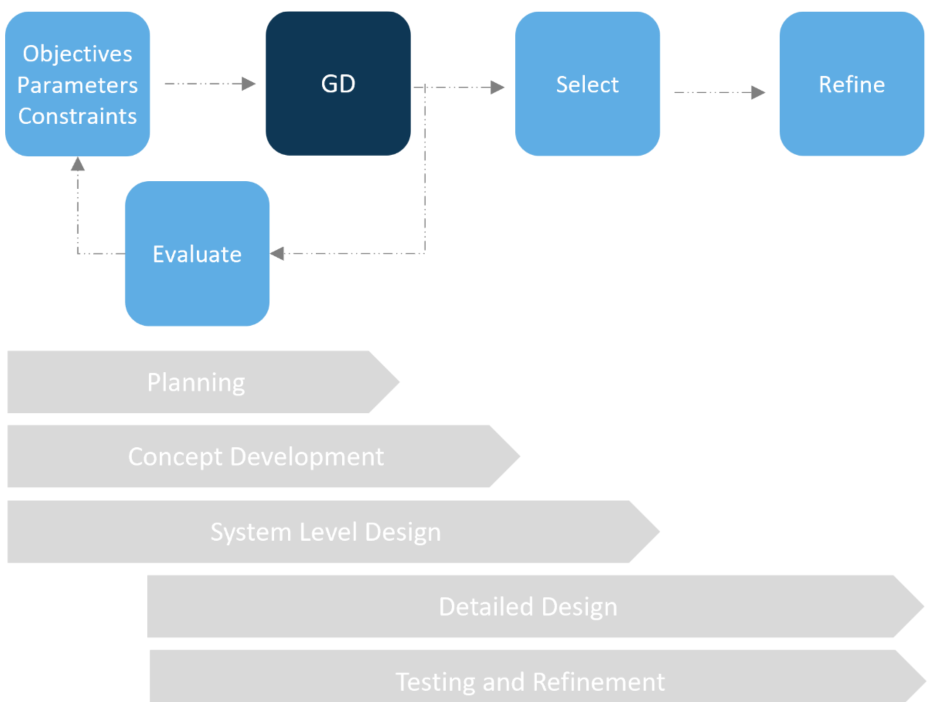


Figure 3-2 : Overlap of generative design (GD) process (top) and a more traditional design process (bottom, adapted from Ulrich et al.). The generative design process allows for traditional design stages to be carried out in parallel.

The use of generative design tools may not always be so straight forward. Many qualitative metrics, such as aesthetics, cannot be directly defined in the generative design tool. Therefore, designers find creative workarounds to control qualitative metrics, such as defining geometry constraints, modifying loading conditions, or manually refining the design outputs of the generative design tool. This gives the potential for a designer's subjective preferences to guide the design solutions. The unique expertise designers apply throughout the design process offers an opportunity for diversity of outcomes between designers. An example of this subjectivity influencing the design outcomes can also be found in GE's GrabCAD challenge [57]. Designers were given an initial geometry, objectives, constraints, and parameters. Despite the same initial design problem, over 700 diverse designs were generated by designers, many using optimization design tools [58]. However, depending on the path each designer chooses to take and their choice of workarounds, subjective input has the potential to lead to design solutions that are not the best solutions for a given design problem. This is especially possible with novice computational designers, who will still be able to generate feasible designs with generative design tools but will not necessarily explore a variety of solutions. On the other hand, computational tool experts can be more creative in their uses of the generative design process to explore the design problem and breadth of design solutions, and to provide inspiration in the early stages of design. This can lead to more innovative and creative design solutions that balance both the performance and non-performance design metrics. All this exploration using the generative design tool and the iterative process to incorporate non-performance metrics can drive up the design time. This could mean that designers spend more time in the early problem definition stage and in the later refinement stages, while less time is spent on generating the designs themselves.

3.6 Conclusion

It is clear from the six interviews of designers that generative design tools have implications for the design process, designer behavior, and design outcomes. The use of generative design tools influences how designers define the design problem and how they use the tool to iterate through the design to achieve both the quantitative and qualitative metrics. Creative uses of the tool by experts have the potential to create innovative and high performing designs. The ability to quickly produce feasible designs through simple inputs to the design tool can affect the design time. The simple inputs into the design tool also allow for more flexibility in the early stages of the project time when performance metrics may continue to change.

There are some limitations in this study that can be addressed with additional work. The findings in this study may be restricted due to the small sample size of interviewees which only allowed for observations of areas in design that may be affected through the use of generative design tools, but the full extent of their affects was not derived from these interviews. Future work can incorporate more interviews to explore the depth of influence of generative design tools on design process and the design outcomes.

The findings from this study provide insight into the implications the use of generative design tools can bring to the design process. Many questions remain as to the extent of the effect generative design tools have on the process; How do the different workarounds to incorporate the qualitative metrics affect the design outcomes? How are the designs created affected by the subjectivity of the designers? What is the distribution of time for each stage of the generative design process, and is it overall shorter than traditional design? What is the flexibility of the generative design process as the project time progresses? This study should be used as a motivation for additional research in each of the design topics presented to further understand the effects of generative design tools of the design process and design outcomes. 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 in the interviews that the quantitative-driven generative design tools did not allow for direct control of qualitative metrics such as aesthetics. However, the designers interviewed all described different ways of incorporating qualitative metrics, such as aesthetics, into the design process. Future experimentation can be used to further observe how designers balance qualitative and quantitative metrics while using generative design tools, and how the use of these tools can affect the performances of the designs generated. The next chapter describes an in-lab experiment conducted to address this implication.

Chapter 4

Balancing Mixed Objectives in Generative Design

4.1 Introduction

The previous chapter established observations on the effects of using generative design tools on the design process and designer behavior. One of the implications derived was a quantitative-driven process that leaves the responsibility of incorporating qualitative metrics on the designer. As one interviewee of the study said,

> *"...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] looking at something that [is] not doable… you have to be able to evaluate from a design perspective and experiential point of view."

As this designer mentioned, it is important to balance both the "design perspective" through the quantitative objective while also balancing the "experiential point of view" encompassed through the qualitative objectives. This sentiment motivates the study described in this chapter to address the following research questions:

RQ1 How do designers balance qualitative and quantitative objectives while using generative design tools?

Design problems are often very complex, with many objectives spanning both quantitative and qualitative metrics [59,60]. These multiple objectives are often more than what can be incorporated in a generative design tool both due to the capabilities of the tool itself and the time it would take to represent the objectives in ways the tool can understand [61]. Therefore, designers must balance the objectives that can be represented in the tool with those that cannot. We would like to understand how these mixed objectives that are partially represented in the generative design tool are considered by designers throughout the design process.

RQ2 How are qualitative and quantitative objective performances affected with the use of generative design tools?

Due to the limitations of generative design tools and the time constraints to represent all the relevant design objectives, designers hold the responsibility to ensure all the design metrics are considered throughout the process either through representation in the generative design tool or manually included through the designer's influence in the process. This can be accomplished through clever manipulation of the design constraints, or manually editing after selecting a design from the generative design tool as explored in previous chapters [27]. We are interested in understanding how this manipulation of the generative design tool affects the performance of quantitative and qualitative objectives. We would like to understand how well designers manage aesthetic objectives, and how these objectives may influence the performance of quantitative objectives.

These research questions are investigated through an in-lab experiment using a generative design tool. Participants are asked to design a canopy that meets both quantitative and qualitative objectives. The process in which designers interact with the generative design tool throughout the design task and the quantitative and aesthetic performances of the generated designs are analyzed.

4.2 Related Work

4.2.1 Levels of Aesthetic Attributes

To understand how designers can incorporate aesthetic objectives into the generative design process, an understanding of aesthetics more generally is needed. One way of describing the aesthetics of a product is as semantic or syntactic. Semantic attributes relate to the subjective interpretation of the gestalt, or overall configuration of a product, to describe how the shape feels to an individual, such as cool, modern, and sleek [62]. In contrast, syntactic aesthetics relate to the product's form elements and configuration, including shape, composition, and texture [62]. Syntactic aesthetics are more objective and can be determined directly by the designer [63]. Examples of syntactic aesthetics terms can include curved, long, and symmetric.

Syntactic and semantic aesthetics can be used to derive three different levels of aesthetic attributes: form (level 1), gestalt (level 2), and interpretation (level 3) [64,65]. The form of the product at the first level is described using syntactic attributes for the shapes of the product features. At level two the product gestalt, or overall visual arrangement and composition of the product as a whole, includes rules of symmetry proximity, similarity, continuance, repetition, and closure [62,64]. The interpretation of the form at level three defines the semantic aesthetics of a product, which can be very subjective and can even differ from culture to culture [66,67].

4.2.2 Measuring Aesthetic Preferences

Understanding the semantic attributes of products has been the focus of many studies to select and refine the product based on user feedback throughout the design process. Kansei engineering offers one approach to understand and quantify a user's semantic aesthetic preferences using the semantic differential method [66]. This method first develops a list of semantic attributes that are related to a product through user surveys and design expert consultation. The semantic attributes are then used in a questionnaire distributed to users to understand their semantic preferences towards a product. For instance, Hsu, et al. used the semantic differential method to describe telephones using images and word pairs. They found that the preferences between designers and users and their interpretations of the image-word pairings differed for the same object [68]. Chuang, et al. used the semantic differential method to understand users' preferences for mobile phones and linked those preferences to the design elements of the mobile phone [69]. Johnson, et al. surveyed design reviews, museum exhibitions and commentary on products to develop a semantic language for aesthetics to describe sensory, symbolic, and stylistic attributes of products [70].

While many studies focus on understanding the semantic attributes of products, some studies also investigated the syntactic aesthetics of products. Breeman, et al. formalized a mapping between the shape of an object and its semantic aesthetic characteristics [71]. Hu, et al. defined several design attributes of cameras, such as body structure and button shape. They varied combinations of the camera attributes to generate several designs with different aesthetics based on the gestalt principles [72]. Similarly, Kobayashi, et al. parametrized the form of a chair using points and curves along the chair back seat. They varied the parametric attributes to generate different forms and then measured the users' aesthetic preferences to semantic attributes such as attractive, cool, and stylish [65].

This study adopts a format similar to the semantic differential method to select syntactic attributes that can be used to describe the aesthetic preferences of canopies. This is used to formulate an aesthetic objective for designers to incorporate into the generative design process.

4.2.3 Aesthetics in Computational Design Tools

Design objectives are often a combination of quantitative and qualitative goals and designers can use generative design tools to create designs that balance these multiple objectives to create better performing designs [73]. However, many generative design tools allow for only quantitative objectives, such as minimizing weight or maximizing stiffness. Qualitative goals, such as aesthetics and other user preferences, are often difficult to quantify and represent in generative design tools [74]. Nonetheless, aesthetics is an important objective and designers often look for ways to incorporate it into the design process.

There has been some research into measuring users' aesthetic preferences and quantifying them for optimization. Lugo, et. al, used product composition through the gestalt principles to quantify aesthetics. They found that products with similar aesthetic compositions were preferred equally by participants [66]. Darani, et. al, used an elimination algorithm and an interactive genetic algorithm to first use participants' scores of designs to then generate designs based on user preferences [75]. Orsborn, et. al, introduced a methodology that uses an atomization of product form to determine attributes for a utility function that can then relate the product form to users' aesthetic preferences [76]. Brintrup, et. al, uses an interactive evolutionary algorithm to optimize qualitative and quantitative criteria simultaneously while designing a manufacturing plant layout [61]. Despite the interest in quantifying qualitative preferences and incorporating them for optimization, these efforts remain limited in their abilities and applications. Qualitative preferences, especially aesthetic requirements, are not easily encoded into the optimization algorithm of generative design tools [74]. Therefore, designers often manually include qualitative objectives in the design process.

Qualitative goals are incorporated by the designer manually through manipulation of the objectives, parameters, and constraints or modified afterwards to achieve the desired qualitative objectives as discussed in previous chapters. This requires designers to make trade-off decisions while using the generative design tool and while considering the numerous generated designs to optimize for both the quantitative objectives within the tool and the qualitative objectives not represented in the tool [74]. For instance, Brown, et. Al, investigated an interactive design process using computational tools and found that designers preferred flexible design environments that gave them freedom and creative control over the designs compared to a completely automated environment [77]. Some tools make it easier for designers to balance the qualitative and quantitative design objectives by diversifying the designs generated by the tool [59]. Other tools ensure diverse results can be easily visualized based on both performance and diverse aesthetics to help designers make design decisions based on aesthetic preferences [78]. This study uses the latter set of tools to generate diverse results and present results quantitatively and qualitatively, leaving the designer to balance the objectives.

4.3 Methods

The study involved 34 undergraduate and graduate students at a U.S University, and industry professionals at design companies. Participants were asked to design a canopy to meet a set of user requirements that included quantitative and qualitative metrics. The design task was done both with and without the use of generative design tools.

4.3.1 Experiment Interface

Participants were given a parametrized canopy, modified from a study by Mueller et al. (2016), designed in Grasshopper powered by Rhinoceros CAD [73]. The canopy design was defined by 10 parameters, as shown in Figure 4-1. The 10 parameters to control the design of the 3D canopy in Grasshopper include the horizontal and vertical length and width, the curvature, the number of supports and the spread between the supports. Mueller, et. al., showed that these variables provide the possibility for a diverse set of designs both in terms of performance and aesthetics [79]. Participants could modify these parameters through sliders, which allowed for quick manipulation of the designs without advanced experience using the design tool [18]. The canopy was constrained to be symmetric to reduce the number of variables while still maintaining enough flexibility to create an aesthetically diverse set of designs.

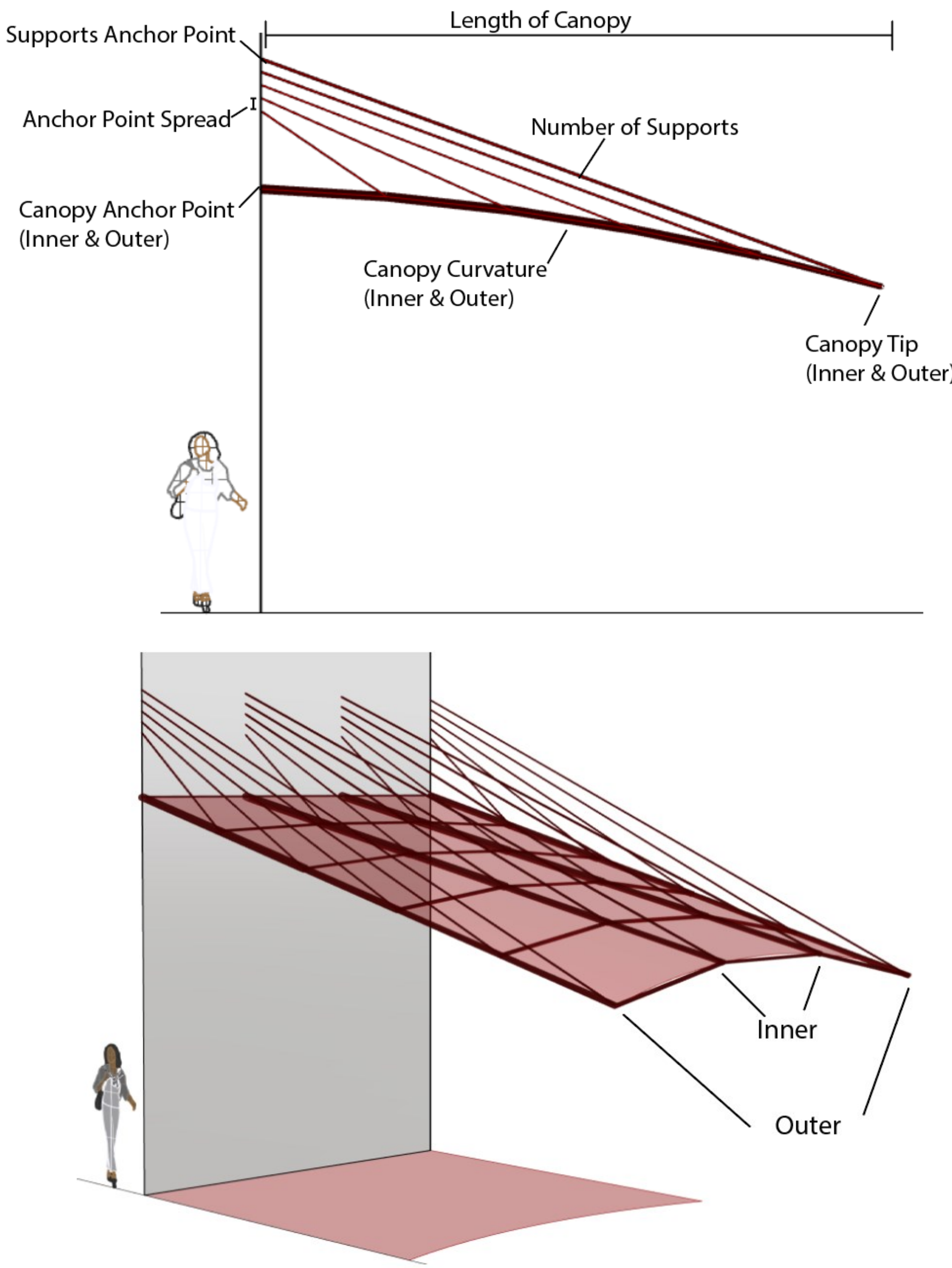


Figure 4-1 Ten parameters controlled by sliders to define the symmetric canopy design [73].

The design objectives were to minimize the shaded area, maximize the weight, and maintain the desired aesthetic of a hypothetical café owner. Participants were shown the current weight and shaded area of the design in the Rhino design space. The performances were also normalized with respect to the best possible value for the objectives so that the best performing design received a normalization of 1, and all other scores were a multiple showing how much worse the design performed with respect to the objective goal. For instance, a normalization score of 2.00 for the weight indicates that the current canopy design is two times heavier than the lightest possible design.

Participants were given a design task to be completed in Grasshopper, once using the traditional CAD method and once using a generative design tool. In the first iteration of the design task, participants manually controlled the parameters via sliders to design canopies that meet the three design objectives. Then designers were asked to complete the design task using a generative design tool while still maintaining control of the variables to modify the designs. The Multi Objective Optimization (MOO) feature of the Design Space Exploration Grasshopper plug-in was used as the generative design tool [80]. MOO is based on an NSGA-II algorithm to optimize the input objectives through the given variables. This algorithm randomly generated the first 20 designs based on the 10 parameters and design objectives of shaded area and weight. The algorithm also ensures diversity in the designs generated, yielding designs that span across the objective space. The algorithm then evaluates the designs for quantitative performance. Features from the top designs are combined to generate a new set of designs. This process is repeated 5 times until 100 total designs are generated. MOO provides the participants with top 20 designs along the Pareto Front that are optimized based on the weight and shaded area objectives. The design tool interface is shown in Figure 4-2.

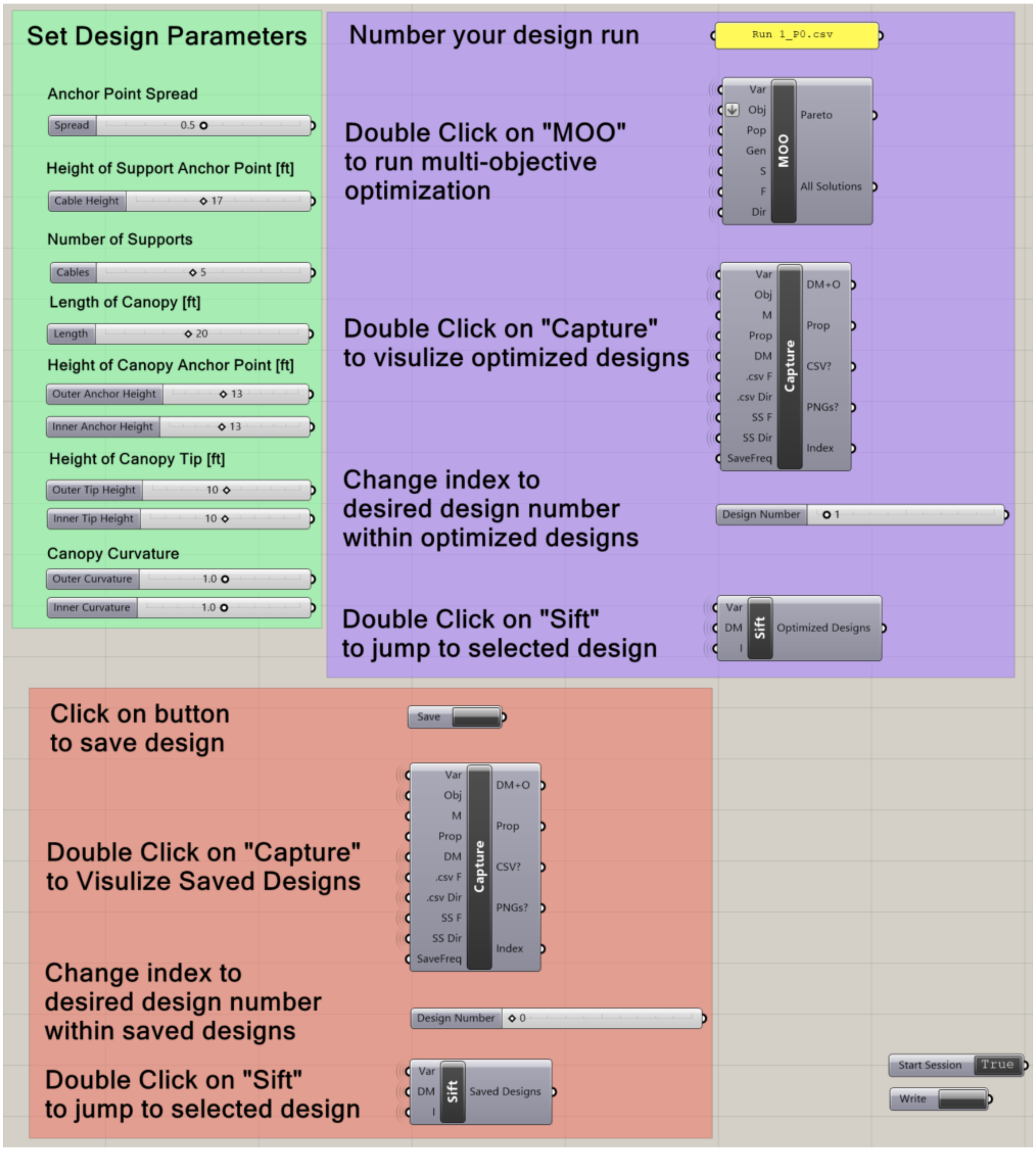


Figure 4-2 Tool interface for MOO design Task. In the Free design Task participants were only given the parameters (green box) and save functionalities (red box). In the MOO design task participants were also given the generative design tool (purple box) [73].

Each participant was given a 5–7-minute tutorial of the given design tools before each design task. The 15-minute design task was followed with a short discussion with the facilitator to allow participants to describe their design process, provide their top 3 designs, and rate their satisfaction with the design outcomes. The experiment stages are shown in Figure 4-3. The experimental protocol for the tutorials of the design tool is included in Appendix C. The pre-survey and post task questionnaire are included in Appendix E and F respectively.

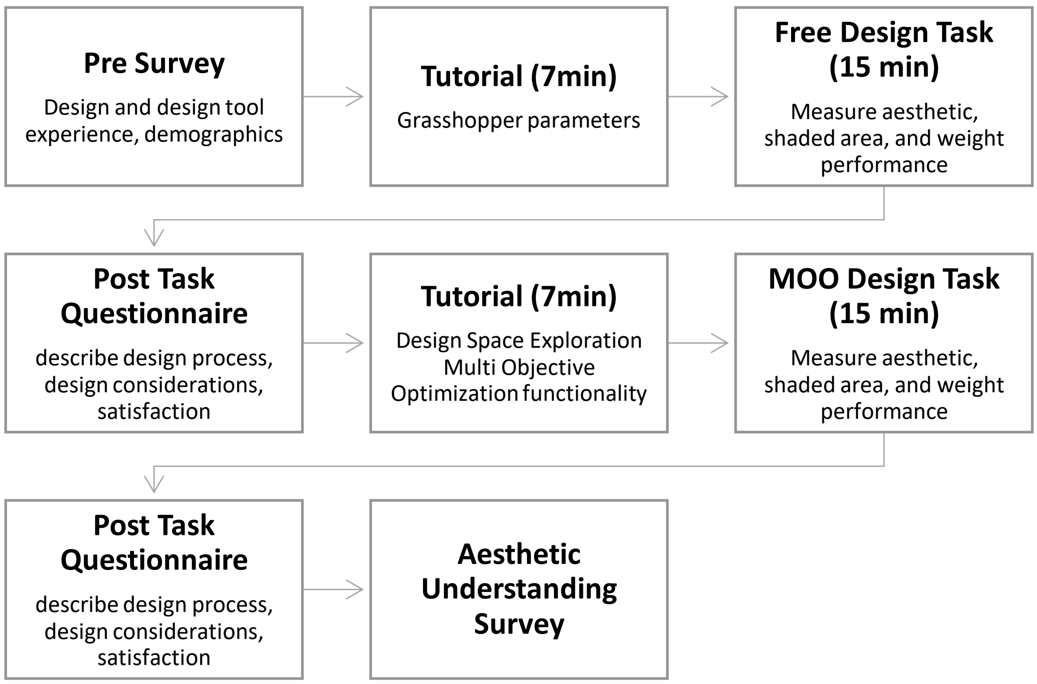


Figure 4-3 Experiment process for each participant

4.3.2 Aesthetic Objective

Typical human machine interfaces include visual graphics, textual explanation, and tangible artifacts [41]. Due to the highly visual aspect of aesthetics in design, methods to visually convey aesthetic preferences were explored [68]. Images of canopies for the aesthetic objective were avoided to prevent fixation on the shape of the given canopy while designing using the parametric model. Instead, vases were used to convey aesthetic intent as they are largely aesthetics, simple functionality, and widely recognizable [69].

Since it was important to clearly convey the desired aesthetic objective, syntactic attributes describing the canopy form were used to objectively define aesthetics and link the desired form to the design parameters. Syntactic attributes were chosen to objectively describe the product form. A list of syntactic aesthetic attributes used to describe the form of products including the shape, such as geometry and size, and configuration, or the arrangement of the shapes, were collected from previous literature [62,64,69–72,81,82]. A total of 101 terms were collected. Similar and synonymic terms were combined to condense the list to 48 overall words that can be used to describe product form. This list of form attributes was presented to 9 designers and design researchers with human-centered design, mechanical engineering, and industrial design backgrounds to refine and categorize the words to create a syntactic aesthetic language that can be used to describe different products. The designers were divided into three teams and were given the 48 words written on index cards. The designers were given one hour to expand on the list of words and to generate categories representing the list of attributes to ensure a comprehensive set of attributes that can be used to describe product form. This exercise was intended to create a final list of syntactic attributes that can be used to describe the form of various different objects. Designs of products embodying different combinations of syntactic attributes can be created to generate a set of designs that are aesthetically diverse. The full list of 67 syntactic attributes is shown in Appendix B

Four attributes with two levels each were selected from the list of syntactic attributes based on their ability to describe the form of vases and canopies: width (wide | narrow), length (long | short), curvature (curved | angular), and complexity (complex | simple). These four attributes with two levels can be combined to create sixteen different designs. It was clear that the aesthetic objectives could be linked to the qualitative performance. For instance, a 'short' canopy would be lightweight, but have minimal shaded area while a 'long' canopy would be heavy but be near optimal in shaded area. Therefore, two versions of aesthetic objectives were used to allow for a better understanding for how designers balance the tradeoffs between the qualitative and quantitative objectives. The first version was short, narrow, simple, and curved while the second version was long, wide, simple, and curved as shown in Figure 4-4. Participants were evenly split between two versions of aesthetic objectives.

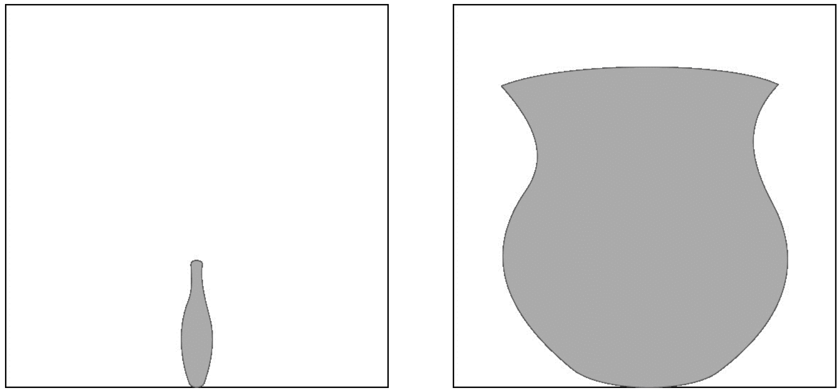


Figure 4-4 Vases used to define the aesthetic objective in version 1 (left) describing a short, narrow, simple, and curved vase and version 2 (right) describing a long, wide, simple, and curved vase

The participants were given a set of 5 vases, one which was the hypothetical user's preferred choice that embodied the aesthetic objectives and four others that differed by only one attribute each, as shown in Appendix D. The images were complemented with text describing the vases based on their syntactic attributes to further explain the aesthetic objectives. The images of vases used were selected from a set of aesthetically diverse vase dataset. This was generated from thousands of 2D images of vase silhouettes collected from online databases and stock images [83,84]. Vases that exemplified the sixteen syntactic attribute combinations were chosen from this set. Three researchers individually characterized the selected vase images based on the four attributes and their respective levels. The researchers reached total agreement on the description of sixteen designs of vases.

4.3.3 Establishing Aesthetic Understanding

While the aesthetic objective was given in image and text format to ensure appropriate understanding, participants may have different levels of understanding of the aesthetic objectives that could affect their overall aesthetic score. Therefore, an additional task was added to the end of the experiment and conjoint analysis was used to assess aesthetic understanding.

Many studies have used conjoint analysis to understand users' aesthetic preferences. Kelly, et al. defined the form attributes of a water bottle through a parametric model using 5 radii, which were varied to generate the different designs. They used rating based conjoint to understand user preferences towards the bottle shapes and found that users preferred shapes they were familiar with [85]. Similarly, Mata, et al. used a parametric model of a vase to generate 90 vase solutions to see the potential of the tool in generating designs of varying forms that can also result in different aesthetic and emotional responses [86]. Sutono, et al. designed chairs using 6 design parameters, each with 3 levels. They used rating based conjoint analysis to understand the emotions evoked with each design [87]. Lugo, et al. measured user preferences to products with similar gestalt and found that products with similar complexity were equally preferred [66]. Chou, et al. used rating based conjoint analysis to measure the preferences of products among different stakeholder groups. They developed the stakeholder agreement metric to evaluate the level of agreement between the groups to help designers make go no-go decisions [88].

In this study, conjoint analysis was used to establish an aesthetic understanding score for each participant. Participants were given 16 canopy designs with varying combinations of syntactic forms and were asked to rate the user's aesthetic preferences for the designs on a scale of 1-5. The rankings of the different combinations of attributes are used to develop a utility function (EQ.1) that represents the individual's preferences to the different attribute levels [88,89]. The coefficient of regression β indicates the direction and magnitude of an individual's preference for each attribute (m) and corresponding attribute level (ki). A positive coefficient represents which of the two attribute levels the individual preferred. The strength of the preference for each attribute level is represented by the magnitude of the coefficient. These utility functions were compared with the given aesthetic objective to develop an overall aesthetic understanding score for each participant.

$$U(P) = \alpha + \sum_{i=1}^{m} \sum_{j=1}^{k_i} \beta_{ij} x_{ij}$$

EQ. 1

U(P): overall utility of product P

α: intercept of linear regression

$\boldsymbol{\beta_{ij}}$: the coefficient of regression associated with the

j^{th} level of the i^{th} attribute

$\mathbf{x_{ij}}$: the j^{th} level of the i^{th} attribute

4.4 Results

Thirty-four participants were included in this study. Most of the participants were undergraduate and graduate students in a United States University, while some were university staff and local designers (30 and 4 participants respectively). The participants ranged from 18-36 years old, with 18 participants identifying as female, 14 identifying as male, and 2 preferring not to say. All the participants had design experience, which ranged from a few months to more than 3 years. All the participants also reported having experience using computer aided design tools, while 10 had experience using optimization tools and 13 had experience using generative design tools.

The participants completed the design task, first designing a canopy controlling only the parameters and then again using a multi-objective optimization tool to assist in the design. Participants were given the same objectives for both design tools; minimize weight, maximize shaded area, and maintain the user's desired aesthetic conveyed through text and images of vases. Participants were equally distributed across two versions for the aesthetic objectives (short, narrow, curved, and simple for version 1 and long, wide, curved, and simple for version 2). At the end of each design task participants were asked to give their top three designs in ranked order of preference to show the cafe owner, to describe their design process, and to rate their satisfaction with achieving the design objectives. The performance of the top canopy design for both design tasks is analyzed in this section.

4.4.1 Aesthetic Performance

The selected designs were independently evaluated by three researchers to assign syntactic aesthetic attributes according to length (long | short), width (wide | narrow), curvature (curved | angular), and complexity (simple | complex). A rubric for categorizing the designs based on aesthetic attributes was agreed upon by the three researchers (Appendix G). Krippendorf's Alpha was calculated to assess the inter-rater reliability. A Krippendorf's Alpha of 0.67 signifies moderate agreement between the three raters [90]. Therefore, the final aesthetic categorizations of the designs are the syntactic attributes with the majority agreement between the raters. Aesthetic scores were calculated based on the ratio of the aesthetic attributes of the designs agreed with the given aesthetic objective for the version given across both design tasks.

A paired two sample t-test was used to evaluate the statistical difference of aesthetic scores between the top designs generated in the Free and MOO design tasks. As shown in Figure 4-5, the aesthetic scores of the designs created in the Free design task are higher on average than in those generated in the MOO design task, however the difference is not statistically significant (p=0.23).

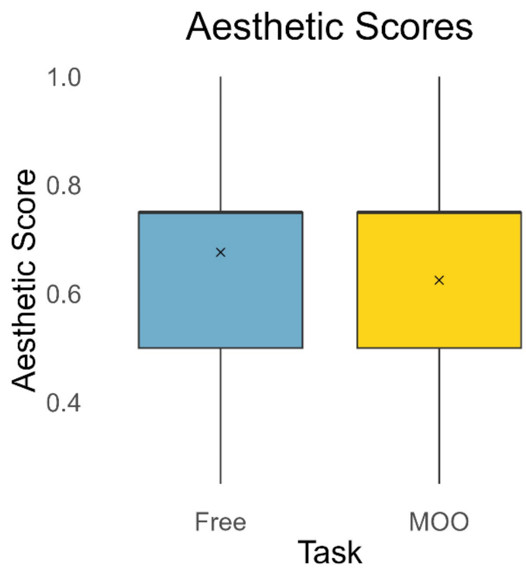


Figure 4-5 Aesthetic Scores of the two design tasks. No statistically significant difference in the aesthetic performances was observed.

Participants' aesthetic understanding of the given objective was calculated using conjoint analysis. After the final design task, participants were asked to rate 16 canopy designs based on what they understood of the user's aesthetic preferences. Utility functions were calculated for each participant based on their ratings of the 16 canopies embodying different syntactic attribute combinations. The signs of the coefficient of regression from the utility function were compared to the given aesthetic objective to calculate an overall aesthetic understanding score. For instance, the utility function in EQ.2 indicates that this participant understood the user's aesthetic preference to be short, narrow, angular, and complex. The given aesthetic objective to this participant was short, narrow, curved, and simple. This indicates an aesthetic understanding score of 2/4 attributes.

.

$U(canopy) = 3.562\ +$

$0.563(short) + \ -0.563(long) +$

$$
\begin{aligned}
&-0.187(wide) + \ 0.187(narrow) + \\
&-0.062(curved) + \ 0.062(angular) + \\
&\ 0.313(complex) \ + \ -0.313(simple)
\end{aligned}
$$

EQ. 2

To account for the effect of the level of aesthetic understanding on overall aesthetic scores, the scores were normalized with respect to the understanding score. A t-test assuming equal variance with a p-value of 0.70 indicates that there is no statistically significant difference between understanding scores of versions 1 (avg 0.72 ± 0.23) and version 2 (0.68 ± 0.21). Some participants exhibited a lower level of understanding than their actual aesthetic score, resulting in a normalized aesthetic score greater than one. Therefore, a step function was used to ensure a range of aesthetic scores between 0 and 1.

As shown in Figure 4-6, there is still no statistically significant difference in aesthetic scores between designs created in the Free design task and those generated in the MOO task after accounting for aesthetic understanding (p=0.134).

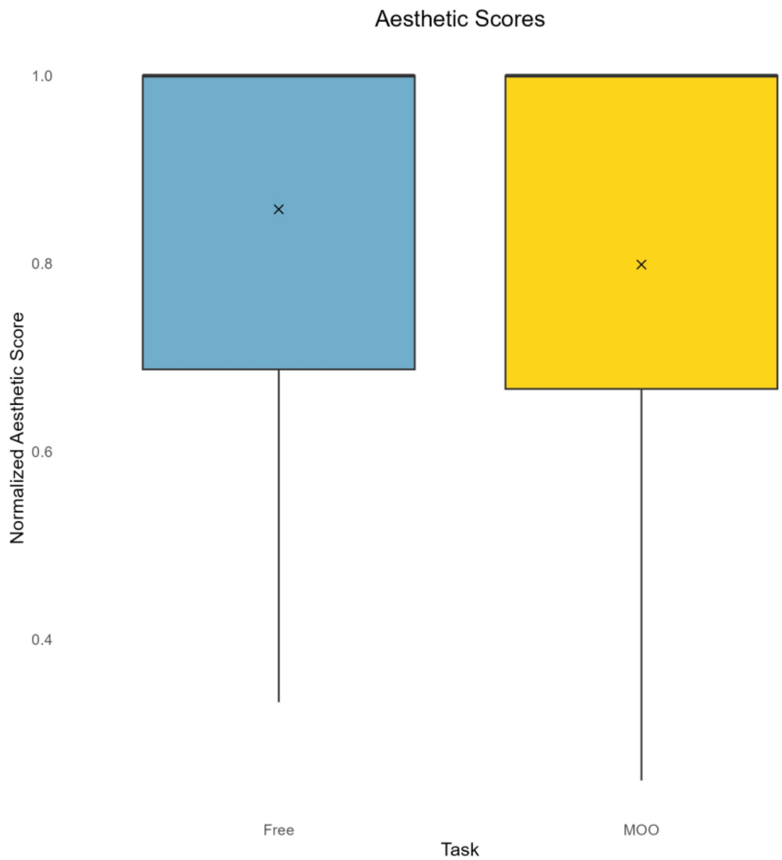


Figure 4-6 Aesthetic Scores of the two design tasks considering the aesthetic understanding of the participants. No statistically significant difference is observed (p=0.134).

4.4.2 Quantitative Performance

The shaded area and weight performances for the selected canopy designs were normalized to the same unitless scale. The global minimum and maximum values for the shaded area and weight of the parametrized canopy were used for normalization based on EQ.3. Thousands of canopy designs were randomly generated to determine the global minimum and maximum values.

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

EQ. 3

The normalized performances of the two quantitative objectives of the top design selected by the respondents are shown in Figure 4-7. A paired two sample t-test was used to evaluate the statistical difference between the two design tasks. While there is no statistical difference in the individual performances of the shaded area and weight (p=0.34 and p=0.12 respectively), the spread of performances in the MOO design task is larger for both objectives. This spread indicates that a larger percentage of respondents performed worse in terms of the shaded area and weight in the MOO design task.

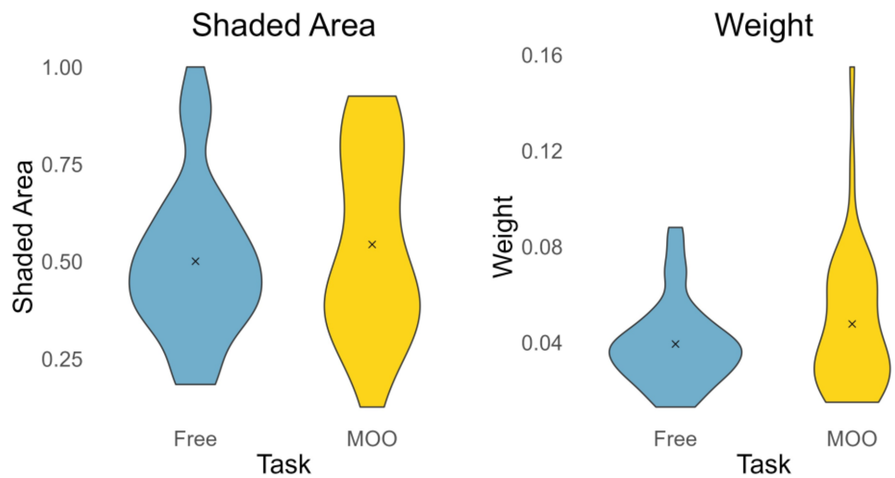


Figure 4-7 Normalized Shaded Area (left) and Normalized Weight (right) performances of the two design tasks

Since the respondents were split into different aesthetic objective versions, a difference in the shaded area and weight performances could be prevalent due to the correlation of the qualitative and quantitative performances. For example, canopies with lighter weight and less shaded area are more in line with the aesthetic objective of version 1 (short, narrow, curved, simple), while canopies with larger shaded area and heavier weight correspond to the aesthetic objective of version 2 (long, wide, curved, simple). Therefore, the ratio of the normalized shaded area and weight was taken to calculate an overall quantitative score (EQ.4).

$$Quantitative\ Score = \frac{Shade_{norm}}{Weight_{norm}}$$

EQ. 4

The quantitative performances are graphed in Figure 4-8. A paired t-test indicates a statistically significant difference in overall qualitative performance (p-value 0.039), with the participants performing quantitatively better in the Free design task than in the MOO design task.

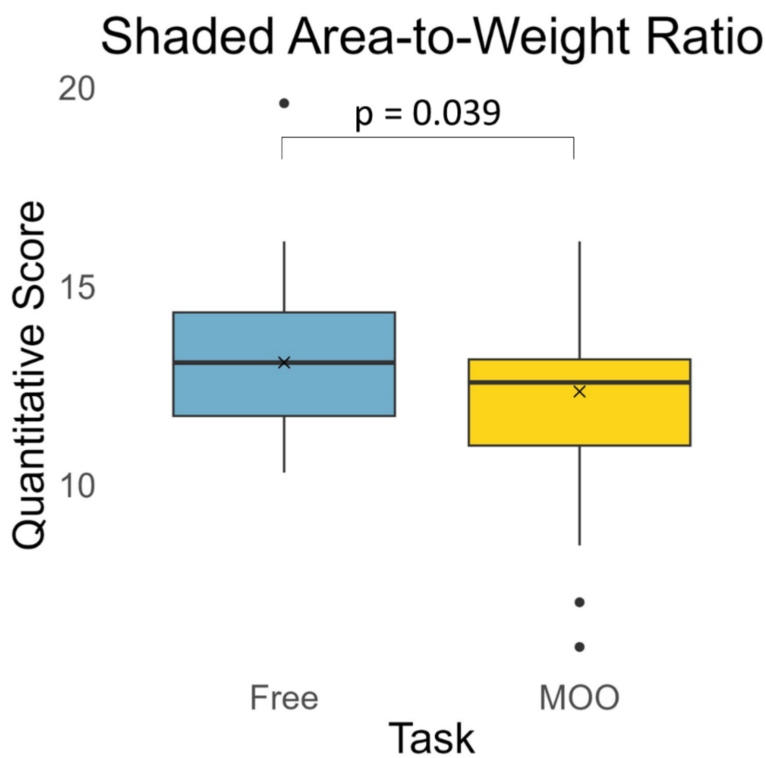


Figure 4-8 Overall Quantitative Scores represented by the Normalized Shaded Area-to-Weight ratio of designs selected in both design tasks. The designs selected in the Free design task have a statistically greater quantitative score compared to those in the MOO design task.

The normalized performances of the two quantitative objectives of the selected designs are graphed in Figure 4-9. The inverse of the shaded area performance is graphed such that minimizing values on both axes indicates a higher performing design with respect to the objectives. In this figure, the best possible weight performance is 0 and the best possible 1/shaded area performance is 1, illustrated as dashed lines in the figure. The performances of the designs generated in the MOO task span a larger portion of the performance space, while the designs generated in the Free design task are clustered to a smaller portion of the pareto front.

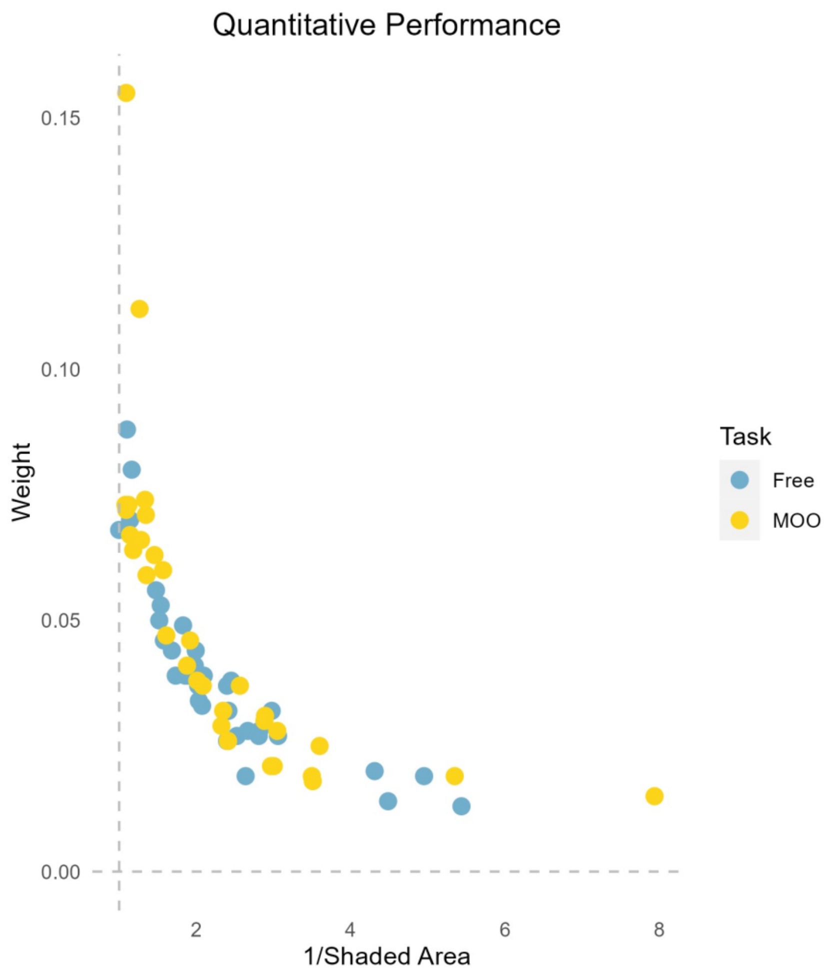


Figure 4-9 Normalized quantitative performances of the designs selected in both design tasks.

The spread of the designs in the MOO design task and the clustering of the designs in the Free design task can be quantified through a calculation of the hypervolume. The hypervolume indicator is a performance metric that gauges the region dominated by a dataset in the objective space, bounded by a selected reference point [91]. This measure considers factors such as the proximity of the points to a Pareto front, the dataset diversity, and the spread of the designs. A reference point of (1,0) was selected as the representation of the ideal design that optimizes both objectives [92].

Using the 'box' method from the hypervolume package in the statistical software R, the hypervolume indicator of the designs generated in the Free design and MOO tasks was calculated [93]. The results revealed a hypervolume indicator of 0.453 for the Free design task and a hypervolume indicator of 1.098 for the MOO task. The larger hypervolume indicator in the MOO design tasks indicates a broader spread and greater diversity of designs that occupy a larger region of the objective space. This is visually evident in Figure 4-10. Conversely, the smaller hypervolume indicator of the Free design task underscores the designs' proximity to the reference point (1,0) which signifies a proximity to optimal performance for both quantitative objectives simultaneously.

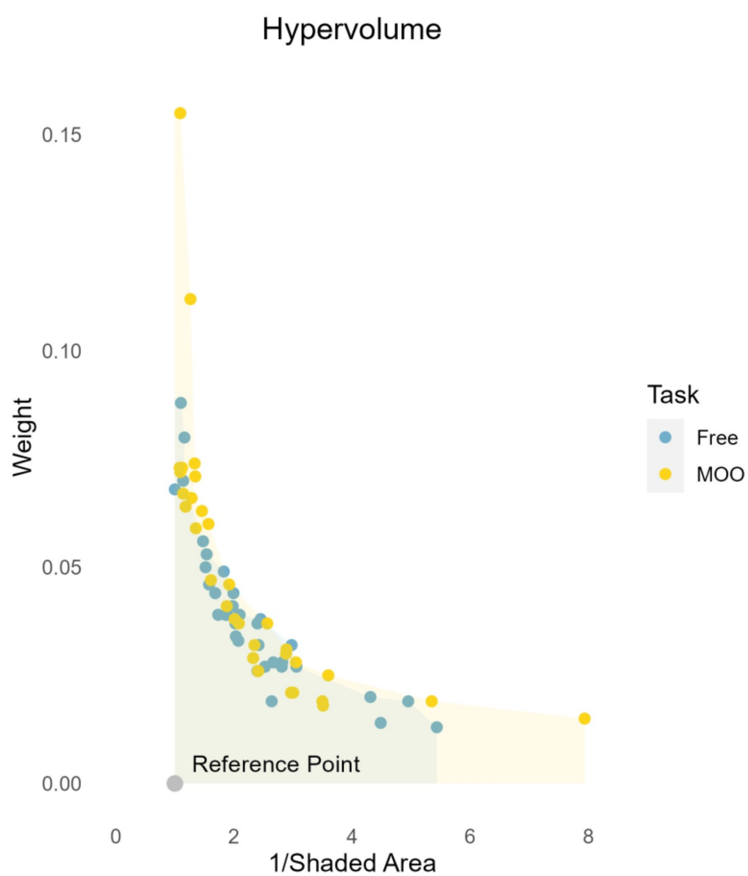


Figure 4-10 Hypervolume of set of designs in both design tasks. Free design task hypervolume is 0.453, MOO hypervolume indicator is 1.098.

4.5 Relationship Between Quantitative and Qualitative Performances

The larger spread of performances may also indicate a larger aesthetic diversity of designs prevalent in MOO since quantitative performances and aesthetics are correlated. This is illustrated in Figure 4-11, in which the majority of the canopies in the Free design task fell under two main aesthetic designs (short, narrow, curved, and simple or long, narrow, curved, and simple). On the other hand, canopy designs in the MOO task were more diversified. Examples of canopies with different aesthetic attributes generated in the design tasks are shown in Figure 4-12.

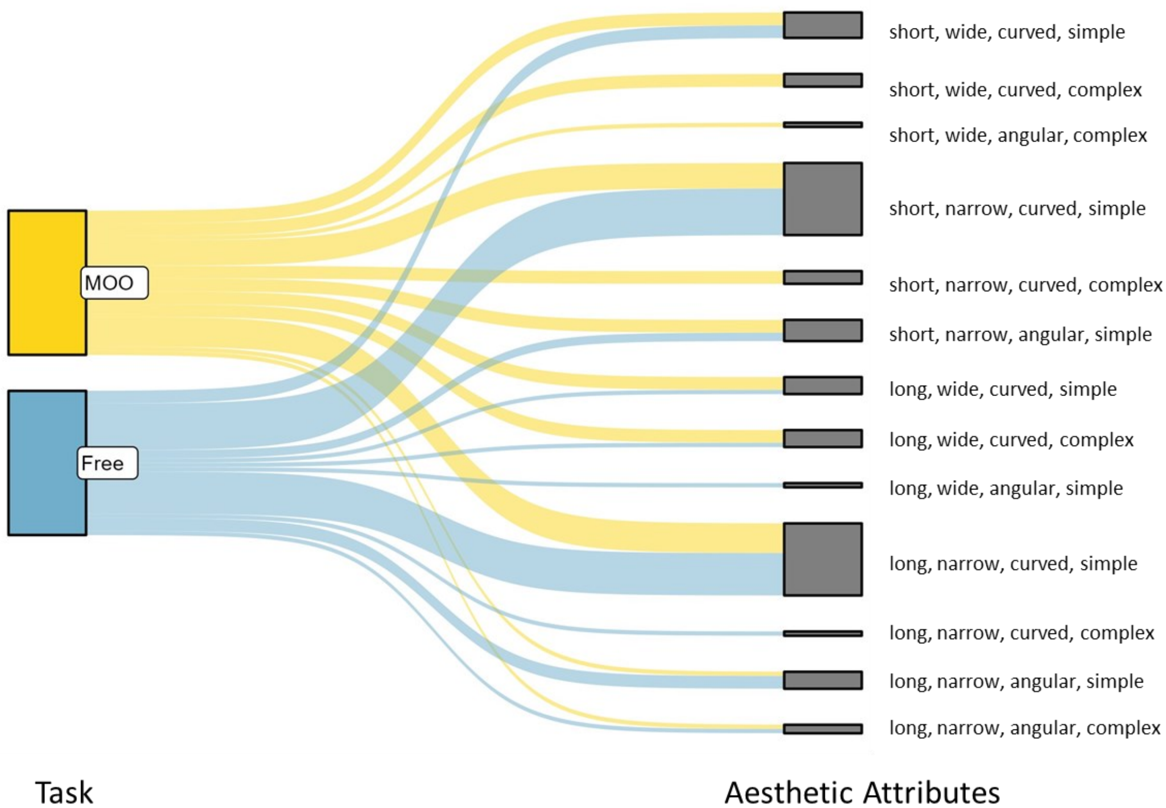


Figure 4-11 Aesthetic characteristics of designs selected in the two design tasks. The dataset of designs in the MOO design task illustrates greater aesthetic diversity.

This aesthetic diversity can further be seen through the Shannon Entropy metric, which employs the probabilities of specific designs appearing in the dataset (P(x)) to measure the overall diversity of the dataset [94]. The Shannon Entropy formula (EQ.5) captures this diversity by calculating the sum of the product of the probability of each design ($P(x_i)$) and the logarithm of its probability.

$$H(x) = -\sum_{i} P(x_i) \log P(x_i)$$

EQ. 5

The resulting Shannon Entropy index indicates the level of diversity present in the dataset. A larger Shannon entropy index signifies a greater diversity of the design set. For the designs generated in the Free design task, the Shannon Entropy is calculated as 2.099 while the designs produced in the MOO design task yield an index of 2.252. The higher Shannon Entropy index observed in the MOO design task reflects a higher level of aesthetic diversity among the designs selected in that task.

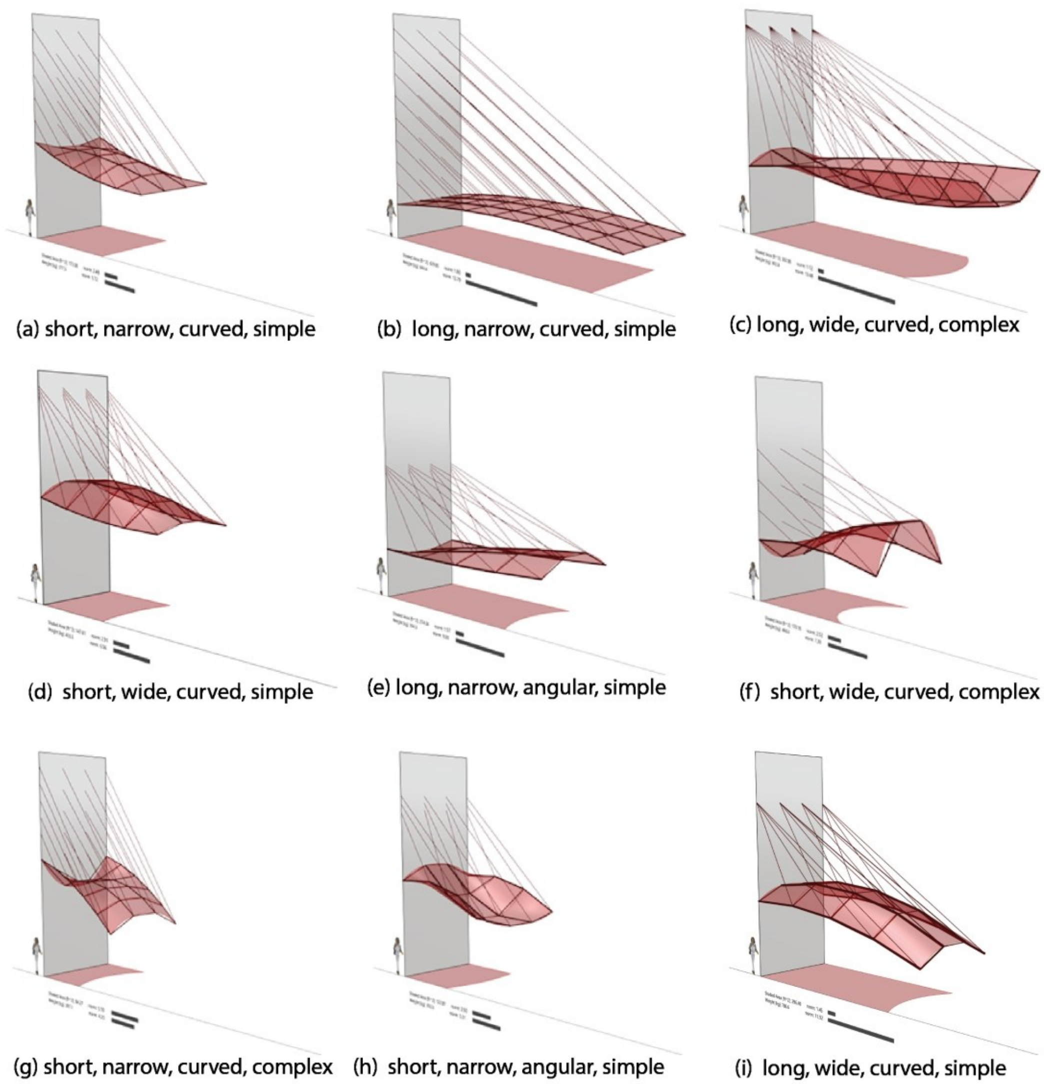


Figure 4-12 Examples of designs selected described by aesthetic attributes.

4.5.1 Performance Satisfaction

After each design task participants were asked to rate their satisfaction with their aesthetic performance, shaded area performance, weight performance, and their ability to balance all three objectives. Participants were asked to rank their satisfaction on a Likert scale ranging from highly dissatisfied (1) to highly satisfied (5). A paired two sample t-test was used to evaluate the statistical difference between the satisfaction in the two design tasks. As shown in Figure 4-13, respondents were statistically more satisfied in the MOO design task in respect to their weight performances (p-value = 6.55 e-3), their aesthetic performance (p-value= 2.44 e-12), and in balancing the three objectives (p-value=6.33 e-4).

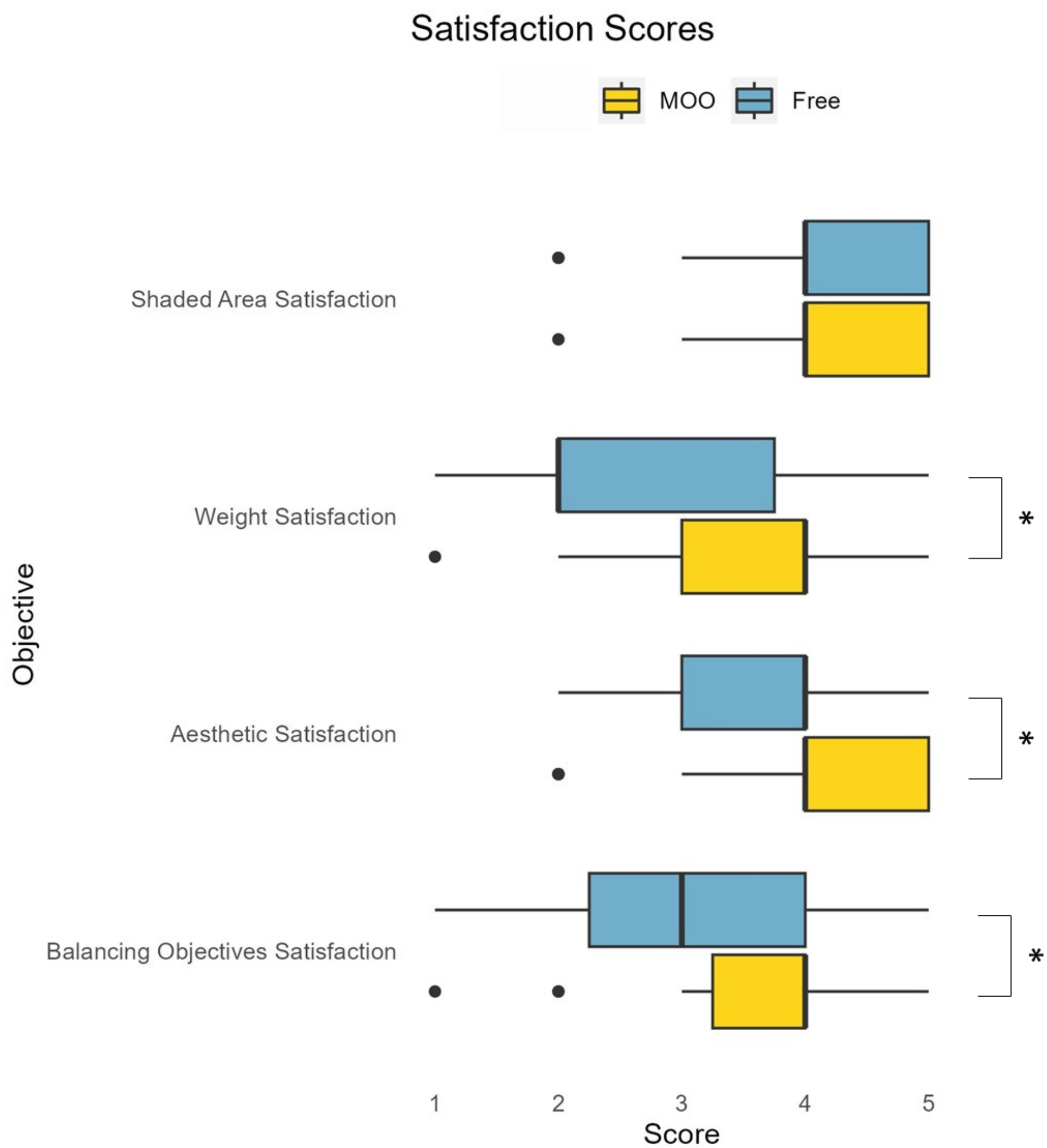


Figure 4-13 Participants' reported satisfaction of achieved the desired (a) shaded area (b) weight (c) aesthetics (d) balancing the three objectives. The asterisks (*) marks statistically significant difference in satisfaction between the Free and MOO design tasks.

4.5.2 Design Process

At the end of each design task, participants were also asked to describe their design process. The recorded responses were transcribed and sorted by a researcher to broadly describe the process based on a focus on quantitative objectives, qualitative objectives, or both simultaneously. This categorization was done for what participants mentioned considering first and what they said they considered second. For instance,

> *"Towards the beginning I started to figure out whether the [quantitative] goals can be achieved at the same time. What does it take to maximize that shaded area and what those designs look like? What does it take to minimize weight and what do those designs look like? They're very much different things and then I started trying to come up with other ways to kind of shrink the design space. I was thinking about typical canopies [that] need to be high off the ground, otherwise people don't fit under it. And other things like that to narrow in [on the design space] and played within those constraints to find a local optimum shaded area and weight while trying to adjust the design to meet the aesthetic preferences of customers."*

was categorized to consider the quantitative objectives first and then the qualitative objectives. On the other hand, another participant described their process as follows:

> *"I ran the MOO, and I looked through all the designs. This time I think what was really helpful was rather than tweaking all these variables to figure out which ones makes both of the [quantitative] norms good, I was able to just look through all the designs generated and kind of narrowed down to the ones that seemed to meet both of the [quantitative] design objectives. And from there, I would click on those and then just modify them very slightly to either very slightly improve the design, like the quantitative design characteristics, and then also tweak it a little bit to kind of more meet the aesthetics but it was very much so just tweaking these designs that were already there."*

This was categorized as considering both objectives first and the quantitative objective second.

The frequency of each categorization is shown in Table 3.

Table 3 Participants' design processes described by what objective they considered first and what they considered second.

	Quantitative First		Qualitative First		Both First	
	Free	MOO	Free	MOO	Free	MOO
Quantitative Second	3	4	10	5	0	4
Qualitative Second	15	5	1	1	1	2
Both Second	1	6	2	4	2	2
Total	**19**	**15**	**13**	**10**	**3**	**7**

Many participants in the Free design task considered the quantitative objectives first and then some made modifications based on the aesthetics. As one participant said,

> *"Towards the beginning I started to figure out whether the [quantitative] goals can be achieved at the same time. What does it take to maximize that shaded area and what those designs look like? What does it take to minimize weight and what do those designs look like? They're very much different things and then I started trying to come up with other ways to kind of shrink the design space. I was thinking about typical canopies [that] need to be high off the ground, otherwise people don't fit under it. And other things like that to narrow in [on the design space] and played within those constraints to find a local optimum shaded area and weight while trying to adjust the design to meet the aesthetic preferences of customers."*

It was also observed that participants optimized the objectives one at a time in the Free design task,

> *"What I did was I picked one as the biggest priority. Optimize that and then from there saw how much can I improve the other two…I guess the big pitfall is as a human I'm only thinking of one thing at a time"*

In the MOO design task, participants described using the multi objective optimization tool to optimize the quantitative objectives, selecting designs that balance the shaded area and weight and then making modifications to improve the aesthetics and/or quantitative objectives further. Some participants trusted the tool entirely to optimize for the quantitative objectives and spent most of their time making modifications for the aesthetics.

> *"I was more concerned with aesthetics at the start this time around [in the MOO design task], just because everything else is very optimized for me and then trying to find a good balance between the other two. So, the weight and the shaded area versus before I think I was more focused on like just one or the other."*

Many participants also described using the MOO tool to obtain an understanding of the different aesthetic possibilities.

> *"I'd say looking at the models that MOO came up with, while a lot of them weren't necessarily the aesthetic that the customer was looking for. It helped me break out of the self-imposed box that I put on myself in terms of what a canopy should look like… some of the more creative shaped ones, I was like, 'oh, I would have never come up with this.'"*

To further understand the effect of the design process on the design objectives, the overall quantitative score and aesthetic scores were statistically compared across the participants based on which objective they considered first in their design process using a one sample t-test. In the Free design task, the respondents that considered the quantitative aspects of the design first had statistically higher quantitative scores (p-value=0.01) compared to those that considered the qualitative aspects first, as shown in Figure 4-14. In the MOO design task, there was no statistically significant difference in quantitative scores between those that designed for quantitative aspects first compared to those that designed for qualitative aspects first. Participants that designed for quantitative aspects in the Free design first had a higher quantitative score than those that considered quantitative first in the MOO design task (p-value=0.038). There was no statistically significant difference in aesthetic scores across the different design process considerations as shown in Figure 4-15.

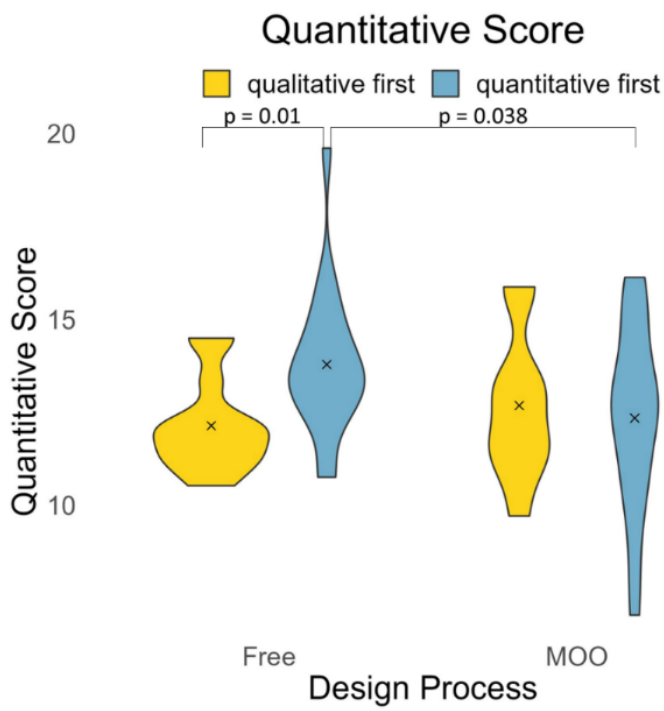


Figure 4-14 Quantitative performance represented by the shaded area-to-weight ratio of the designs based on the participants' description of their design processes.

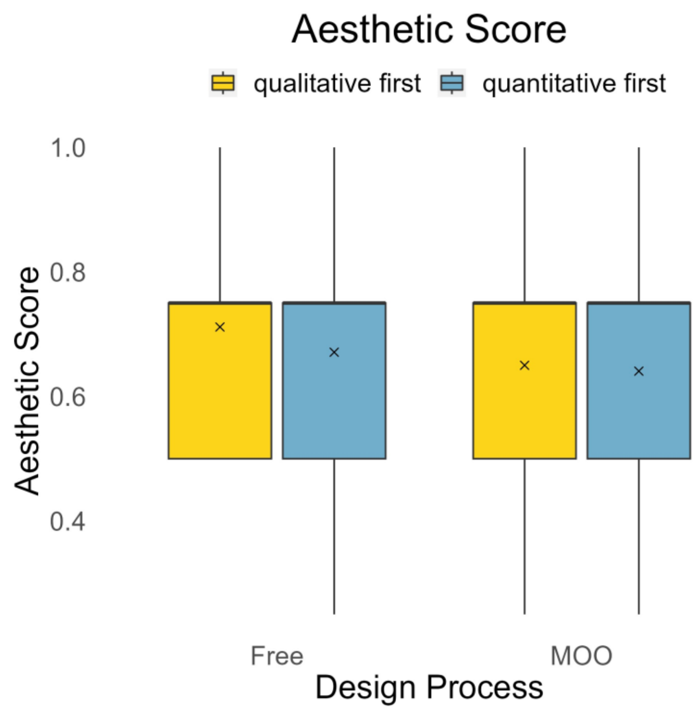


Figure 4-15 Aesthetic performance of the designs based on the participants' description of their design processes.

4.6 Discussion

An in-lab experiment was used to understand how designers balance mixed objectives while using generative design tools. The research questions are addressed through the experiment as follows.

RQ1 How do designers balance qualitative and quantitative objectives while using generative design tools?

A difference in which designers approached the design process was observed between the MOO and Free design tasks. In the Free design task, most participants mentioned optimizing for one objective at a time. Many concentrated on optimizing the quantitative objectives first, focusing on minimizing the weight and/or maximizing the shaded area. For many participants, the aesthetic considerations came second, and for others it was not even considered. On the other hand, more participants considered qualitative objectives in the MOO design task. Participants mentioned trusting the MOO tool to optimize for the quantitative objectives and spent their time selecting and modifying the designs based on aesthetics. The difference of design processes is also shown in the statistically greater quantitative performance of the designs generated in the MOO design task compared to those selected in the Free design task. Although the optimization algorithm only ran for one minute and thereby generated designs that were not the most optimal, many participants trusted the tool to consider the quantitative objectives and did not spend much time modifying the designs to make them more optimal. This ability to distribute the objectives between designer and design tool alleviated the cognitive load on designers attributed to considering multiple objectives at once, leading to a statistically higher satisfaction of achieving the desired objectives amongst the designers in the MOO design tasks.

The different processes described by the participants also correlated with the overall performances of the designs selected in each of the design tasks. Participants that described focusing on the quantitative objectives first in the Free design task had statistically higher shaded area-to-weight ratio compared to participants that described focusing on qualitative objectives first. Conversely, the different design approaches in the MOO design task did not yield a statically significant difference in the shaded area-to-weight ratio of the designs selected. This can be attributed to the tool itself, which considers the quantitative objective even if the designers are not incorporating it throughout the design process. Therefore, the use of generative design tools ensures that the quantitative objectives are always being considered to some extent throughout the process. On the other hand, generative tools do not consider the aesthetic objective, and the incorporation of these qualitative objectives is the responsibility of the designer. The results from this experiment illustrate no statistically significant difference in aesthetic scores for those that focused on quantitative objectives first versus qualitative objectives in both design tasks. This may indicate that the aesthetic objective is considered by the designers in both of the design tasks. Since the designers are manually considering the aesthetic objective in both design tasks, the aesthetic performances of the selected designs are not expected to be different.

Despite the equivalent aesthetic performances of both design tasks, the participants were statistically more satisfied with achieving the desired aesthetic in the MOO design task. Participants described using the MOO tool to discover the aesthetic possibilities and expand on the creativity of their designs. This exploration is illustrated through the greater aesthetic diversity and the larger spread of the quantitative objective space of the designs generated in the MOO design task.

RQ2 How are qualitative and quantitative objective performances affected with the use of generative design tools?

The different ways in which the participants balanced the objectives throughout the design process affected the performance of the design outcomes. Overall, a larger percentage of participants had better shaded area and worse weight in the MOO design tasks compared to the Free design. This indicates that some participants prioritized the shaded area objective over the weight objective. Many participants mentioned doing so since a canopy with no shade is not functionally helpful for the user. Additionally, due to the nature of the parametrization of the canopy, the weight objective was more sensitive to changes in the variables, potentially making this objective harder to optimize for. The greater spread of the shade and weight performances observed in the MOO design task may also be correlated to participants choosing designs based on aesthetics, as was mentioned by many participants. The higher shaded area and heavier weight is especially true for participants that had version 2 of the aesthetic objective, in which participants were asked to design a larger, curved, and simple canopy. This may indicate that participants were designing with aesthetics in mind in the MOO design task, resulting in larger canopies with a greater shaded area and heavier weight.

The performances of the canopies selected in the two design tasks show several instances in which the tradeoffs between the two quantitative objectives were considered more in the Free design task. For instance, one canopy selected in the MOO design task achieved nearly maximum shaded area but had the highest weight overall. Another canopy chosen in the Free design task also had the highest shaded area possible, but at half the weight compared to the design in the MOO design task. There are several other instances in which the designs selected in the MOO design task were equivalent to other designs generated in the Free design task in one objective, but worse in another objective. This can be attributed to the participants' greater focus on aesthetics during the MOO design task, leaving the generative design tool to optimize for the quantitative objectives. The MOO design tool also showed the participants a greater spread of designs that were along the pareto front, showcasing the extremes of the design space. The participants were more likely to explore the extremes of the design space in the MOO design task rather than fixating on a specific region of the objective space as was done in the Free design task.

The MOO design task also included designs with a larger spread in both the aesthetic and quantitative performances as illustrated through the larger Shannon Entropy index and greater hypervolume indicator. This illustrates a greater aesthetic diversity of designs generated in the MOO design task, although that did not translate to greater aesthetic performance when compared to the Free design task. It also indicates a larger exploration of the objective space by participants in the MOO design task. While the Free design task mainly yielded canopies with two combinations of aesthetic attributes, the canopies selected in the MOO design task embodied more aesthetic attributes. Many participants also mentioned that they liked using the MOO tool since it showed them aesthetic designs that they did not consider before. It also allowed them to trust the tool for the quantitative objectives and spend more time adjusting the design for the aesthetics. These findings showcase the potential of generative design tools to distribute roles between the designer and the design tool, allowing designers to spend more time considering other objectives of the design problem such as aesthetics. Generative design tools that ensure diversity of the optimized design set presented to the designers can inspire creativity in the process and provide the opportunity for more unique design outcomes.

4.7 Conclusion

Design problems often consist of both quantitative and qualitative design objectives. Traditionally, designers balance these mixed objectives throughout the design process. Generative design tools offer the opportunity to augment the designer. These tools typically optimize designs for quantitative objectives, leaving designers the task of incorporating qualitative objectives such as aesthetics. This study uses a human subjective experiment of 34 participants given a design task of quantitative and qualitative objectives to further our understanding of how designers using generative design tools balance these mixed objectives. Using traditional design tools, designers manually optimize for the objectives, typically focusing on one objective at a time. Most designers also prioritized quantitative objectives over qualitative objectives. On the other hand, designers using generative design tools were able to trust the tool to optimize the quantitative objectives and spent more time focusing on qualitative objectives. They were also more satisfied in their ability to balance the mixed objectives when using the generative design tool. In both design tasks, designers were manually incorporating the aesthetic objectives, resulting in statistically similar aesthetic performances. However, participants mentioned using the generative design tool to explore more aesthetic possibilities, which is illustrated in the greater aesthetic diversity of the designs created using the generative design tool.

There are some limitations to this study that can be addressed with future studies. While all the participants had experience using CAD tools, many had not used the given generative design tool before the experiment. Expert users of the generative design tool may know the capabilities and limitations of the tool more extensively, leading to different interactions of the generative design tool to balance the mixed objectives. Due to the limited number of participants, the order of design task was kept consistent. Future studies can alternate the order such that some participants use the generative design tool first, thereby parsing out any potential learning effects the tools may have on the designer. Additionally, participants used a generative design tool in which the objectives, parameters, and constraints were already given to them, and the use of the design tool mainly focused on the design generation and refinement stages within a staged design problem. The algorithm also only ran for one minute, which resulted in designs that were not truly quantitatively optimized. Many participants took these designs as a starting point and modified the designs to improve the aesthetics or quantitative performance. While this simplified design task provides an indication for how designers may behave in practice, longitudinal studies of real-world design projects that expand the entire design process can be used to further our understanding of designers' uses of generative design tools.

Chapter 5

Contributions and Future Work

This dissertation addressed the use of generative design tools from a designer and process perspective. The first chapter established the emergence and applications of generative design tools in research and industry. The following chapter outlined a grounded theory approach in which designers that use generative design tools were interviewed to establish a generative design process. Chapter 3 utilizes qualitative research methods to understand the implications of using generative design tools on the design process and designer behavior. Chapter 4 delves deeper into one of these implications by using an in-lab experiment to investigate how designers balance quantitative and qualitative objectives while using generative design tools and how the use of the tool affects the outcome performance.

There are two overarching contributions of this dissertation. First is an understanding of the generative design process and the implications of using generative design tools, which can be used by designers to understand how to make the most of these tools and by designers of generative design tools to know how they are being applied. The second is a deeper understanding of how designers balance mixed objectives. Through this study, a methodology for conveying aesthetic preferences through syntactic attributes was also established. This was used to convey the aesthetic objective to participants through the use of vase images and descriptive text.

5.1 Generative Design Process and Implications

A generative design process was developed through the experiences of six multidisciplinary designers using commercially available generative design tools. This process included explicit stages of the tool and the designer as well as implicit stages. such as the designer inputting their expertise into the process and the generative design tool giving designers an understanding of the design problem and solution space. Designers begin the design process by using their expertise to specify the objectives, parameters, and constraints associated with the design problem. The generative design tool uses these inputs to generate designs that satisfy the requirements. Designers evaluate the tool outputs based on quantitative and qualitative metrics and iterate on the inputs to the tool. This iterative interaction with the generative design tool gives the opportunity for designers to learn about the problem space and solution space. Designers will then select and refine designs, often incorporating qualitative metrics as well. This constraint driven design process requires designers to think about the design problem differently, approaching the process with an abstraction of the design requirements rather than a focus on the physical design of the process. Designers can also be creative in their use of the generative design tool to learn about the design problem and solution space, and to provide inspiration in the early stage of design.

The findings illustrate the importance to understand the distribution of roles of the human designer and generative tool based on the expertise of each. It is beneficial for designers to understand what expertise they can bring to the process and how their own backgrounds can bias the design outcomes. For example, their own experiences and knowledge are critical in setting up the design problem and evaluating the designs generated by the tool. It is also for this reason that the generative design process is still designer-driven, and the designs created through this process are still heavily influenced by the designer. This understanding of the process is also beneficial for designers to appreciate how they can use generative design tools, beyond simply to create a product. The tool can be used creatively as a source of inspiration during ideation, or to learn about the constraints of the design problem and how they may affect the design outcomes. The key takeaways from this contribution are summarized as follows:

- The use of generative design tools offers unique outcomes in the design process, such as understanding what the design constraints are and how they can influence the design outcomes. Designers can take advantage of this to develop an understanding of the design problem.
- Generative design tools output many designs that fulfil the given design requirements. Designers can use these designs to understand the potential solution space.
- The observed implications of using generative design tools indicate areas that designers that use generative design tools and those that develop the tools can investigate in future research. For instance, developers of generative design tools can investigate how designers incorporate design requirements that cannot be directly represented in the tool (such as aesthetic metrics) to further understand how generative design tools can be improved to support the design process.

5.2 Balancing Mixed Objectives using Generative Design Tools

An in-lab experiment was used to observe how designers balance quantitative objectives that can be represented in generative design tools and qualitative objectives that are only included through the designer. Using traditional design tools, designers manually optimize for the objectives, typically focusing on one objective at a time. Most designers also prioritized quantitative objectives over qualitative objectives. On the other hand, designers using generative design tools were able to trust the tool to optimize the quantitative objectives and spent more time focusing on qualitative objectives. They were also more satisfied with their ability to balance the mixed objectives when using the generative design tool. In both design tasks, designers were manually incorporating the aesthetic objectives, resulting in statistically similar aesthetic performances. However, participants mentioned using the generative design tool to explore more aesthetic possibilities, which is illustrated in the greater aesthetic diversity of the designs created using the generative design tool. The results from the study illustrate the potential of incorporating generative design tools in the design process to allow designers to balance mixed design objectives more easily. The delegation of responsibility of design objectives to the generative design tools allows the designer to spend more time designing for more qualitative objectives such as aesthetics. This could allow for a more thoughtful design process in which other aspects of design often overlooked due to time constraints can be meaningfully considered. Generative design tools also offer the opportunity for a more expansive exploration of the design space, potentially leading to more creative design outcomes.

However, not all generative design tools function in the same way and the generalizability of these results may be limited. The experiment used the Design Space Exploration Grasshopper plug-in that employs a Multi Objective Optimization tool based on an NSGA-II algorithm. This tool ensures a diverse set of optimized designs along the pareto front is presented to the designer. Generative design tools that do not generate diverse designs may not produce the same designer behaviors and performances of design outcomes observed in this experiment. For designers that create generative design tools, the results in this dissertation display the usefulness of developing generative design tools that consider the diversity of optimized outcomes, giving designers the opportunity to balance mixed objectives throughout the design process. The takeaways from this contribution are as follows:

- The use of generative design tools can influence the decisions designers make in selecting and refining designs. For instance, participants in this study using generative design tools selected top designs that were aesthetically more diverse and spanned a greater area of the objective space compared to traditional design methods.
- Generative design tools that produce aesthetically and quantitatively diverse results can reduce the cognitive load on designers to incorporate all design requirements and allow for greater consideration of design objectives.

- Designers should be aware of how the generative design tool works to be able to use it appropriately. Blinding trusting the tool to optimize for certain objectives can lead to lower performances.

5.3 Framework for Understanding Aesthetic Preferences

Through the experimental set-up of the in-lab experiment with generative design tools, a framework for conveying aesthetics using form attributes embodied through 2D objects was established. Several different efforts have gone into assessing visual design in a methodological way, in part to come up with a consistent vocabulary for design which could be useful for human designers as well as a way to prompt computational systems for design synthesis [9,10]. In this study, we proposed a new method for generating such a vocabulary. This method draws on the syntactics of visual aesthetics which describe a product using form-related words such as curved, long, and symmetric. This syntactic terminology can be linked directly to the product features, allowing designers to directly apply their understanding of syntactic preferences to the physical design.

The syntactic attributes were applied in three different methods in this study. First, vases embodying different combinations of syntactic attributes were used to convey the desired aesthetic of the hypothetical user to the participants. The syntactic attributes were also used to categorize the generated canopies based on form to derive an overall aesthetic performance of the design. Finally, conjoint analysis was used to quantify individuals' preferences to form attributes. These methodologies of applying syntactic attributes to understand and convey aesthetics has many applications. Product designers may consider users' aesthetic preferences throughout the design process, which is a subjective process that involves interpretation [6]. Not surprisingly, users and designers may perceive the same product differently and the aesthetic goals of designers may be different than those of users, which may bias the designers' understanding of the user's aesthetic preferences [7,8]. Therefore, it can be beneficial to understand and objectively characterize users' aesthetic preferences towards products using syntactic attributes to allow designers to develop products that align with users' aesthetic preferences [4]. A summary of this contribution is as follows:

- Syntactic attributes can be used to objectively define a product's aesthetics. This can be used to understand an individuals aesthetic preferences based on product form.
- These attributes can be linked to parameters of a product's form. Different combinations of syntactic attributes can be used to generate an aesthetically diverse design set.

5.4 Future Work

Future research can explore the other implications of using generative design tools uncovered in this dissertation. This understanding can be vital in knowing the influence of these tools on designer process, designer behavior and design outcomes to benefit designers, educators, and tool developers. The potential of using generative design tools to understand the design problem and solution space can be explored to allow designers to expand their use of the generative design tools. The use of the tools in brainstorming and ideation phases can be studied to understand how generative design tools can be used to inspire creativity in early-stage design.

The constraint-driven process requiring a different way of thinking throughout the design process may affect design education to incorporate these tools. Students will need to be taught to be designers of constraints, understanding how to abstract a problem to its objectives, parameters, and constraints, and how to iterate on the design inputs to affect the tool outputs. More importantly, students will need to understand how to evaluate the tool outputs appropriately. They must learn how to develop an adequate understanding of generative design tools capabilities to ensure an appropriate level of trust in the tool to avoid misuse or disuse of generative design tools.

Finally, understanding how designers interact with generative design tools can further assist in the development of these tools. Observing the workarounds designers use to influence the outcomes of the tool may indicate areas in which design tools can improve to better support designers. Furthering our understanding of generative design tool capabilities will help us appreciate how best to distribute roles between human designers and generative design tools. Furthermore, acknowledging the biases the designers bring to the process and what the limitations of generative design tools are can help us ensure a just design process where all design requirements are given rightful considerations. Through these advancements, generative design tools can be used to augment human designers to generate high performing products that include greater consideration of quantitative and qualitative objectives.

Appendix A Interview Questions

The interviews conducted with the six designers using generative design tools were open ending interviews to discuss the designer's process. Many of the questions were related to the content that was discussed during the interview. Some questions include:

<u>Demographic Questions</u>

1. Degree
2. Previous projects, work experience
3. Years of experience using specific tool
4. Years of experience using computational tools

<u>Project Specific Questions</u>

1. What project are you working on?
2. What are the goals of the project?
3. Can you walk me through your design process for this project? Using your particular design tool. Ask why for every step/decision.
    a. How did you decide on the specifications that were inputted into the tool?
    b. Did you find any criteria that were not obvious to input in the tool, things you may have designed for intuitively?
    c. How do you define when a product is finished?
    d. Did you change the design that was outputted from the software?
4. How many times did you iterate? How long did it take?
5. Did you revisit the specifications set at the beginning?
6. Are there any compromises you had to make in the final design?
7. Was the final design different from what you first imagined? In what ways?
8. If you were teaching a novice designer how to use this tool / design what you did, what would you suggest?

<u>Design tool questions</u>

1. What design tools do you use?

2. Why do you use this particular tool?
3. How often do you follow the software suggestions without any changes?
4. Are there ever times you become frustrated with the software you are using?
    a. If so, why?
    b. What do you do?

Final Questions

1. Do you know anyone else that uses computational tools in design who I can reach out to?

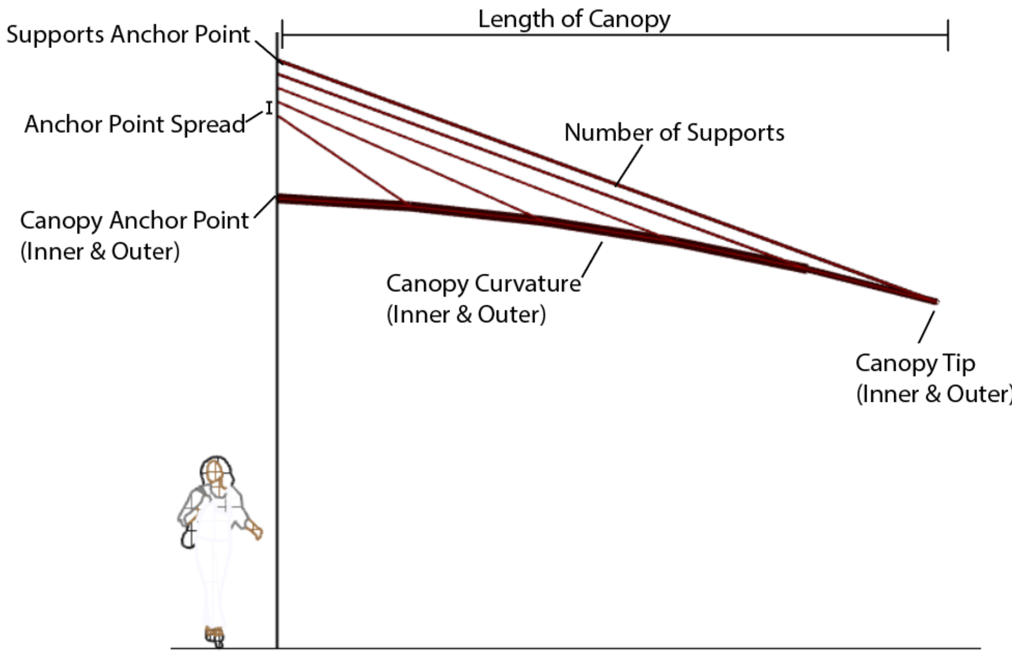
Appendix B Syntactic Attributes

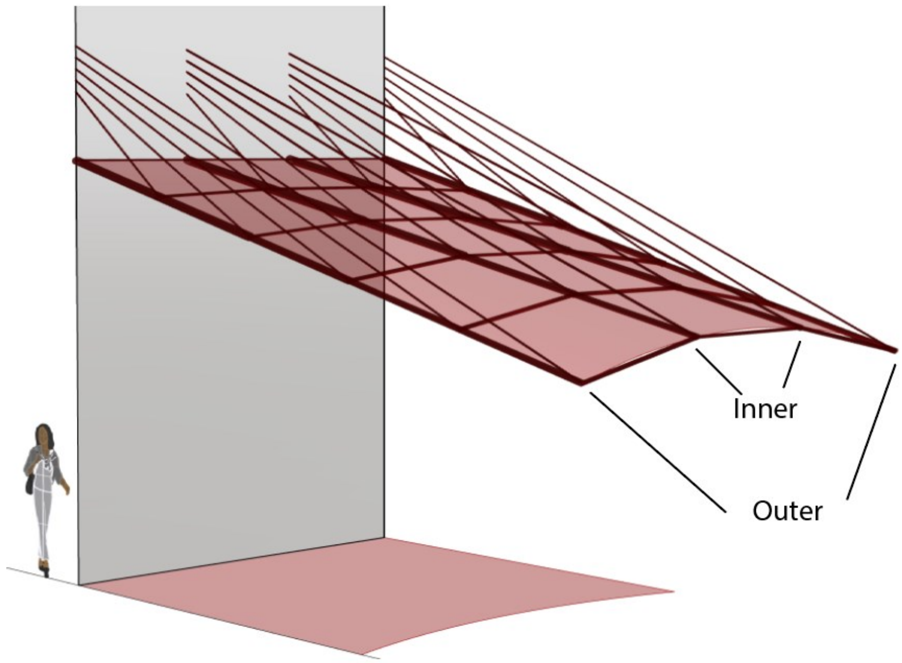
Complexity / Uniformity	Dimension / Size		Cohesion	Shape / Curvature		Texture	Strength	Color
	Length	Volume		Geometry	Connectedness			
complex- basic/simple/unadorned	long/tall - short	big - small	balance	angular - curved	closure - open	smooth - coarse	fragile - robust	
homogenous/unity - varied	narrow - wide	heavy - light	symmetry	rectangular - circular	connected	soft - rough	light - heavy	
	elongated - squat	deep - shallow	proportion	geometric - organic	continuance	fine - grainy	weak - strong	
	thick - slender	compact	unity	bony - rounded	hollow	dull - sharp	delicate	
	low	large		sharp - straight		fuzzy - smooth	taut	
	fine	fat		squared - flowy		bumpy		
	flat	expansive		flat				
	petite			loose				
				sleek				
				taut				

Appendix C Experiment Protocol

Intro to Design Task

You were hired by a cafe owner to design a canopy for an outdoor seating area of their cafe. The canopy is constructed from beams suspended out of the cafe exterior and held by a series of supports. The canopy design is defined with the following parameters shown in the figure:





The cross section of each beam is automatically selected to maintain an acceptable overall deflection, so you can assume that all of the designs generated will be structurally possible. A person is included in the model for scale.

Task Instructions

For the canopy design, the cafe owner is interested in achieving 3 main goals:

- Minimizing the **weight** of the canopy. Weight is important to our cafe owner since it is linked to many other factors such as cost and carbon footprint.
- Maximize the **shaded area** provided by the canopy to allow for the most possible customers.
- Maintain the desired **aesthetics** as described above.

Now your goal is to come up with as many canopy designs as you can for the cafe owner that meet the three objectives. You will have 15 minutes for this design task. In the end we will ask you to select your top three designs to share with the user.

Tutorial Instructions For Facilitator

This canopy is designed in Grasshopper powered by Rhino CAD software. You will have the first few minutes to familiarize yourself with the software.

On the left is Grasshopper, where you can control the different parameters via the sliders. The design parameters are located in the green box. You can move the slider left and right to change the value of each parameter. Make sure the mouse cursor is displaying an arrow to move the slider. Go ahead and play around with the design parameters.

If you click on a box in the grasshopper space you may find many lines appear on the screen. Simply click anywhere in the gray space to make the lines disappear.
On the right hand side is the Rhino design space. You can pan around in this space by right clicking with your mouse and moving around.

give participant a minute to start using the sliders.

In the Rhino design space on the right hand side you can also see how the current design performs with regards to the shaded area and the weight. Two numbers are reported to you, the first is the current shaded area in ft^2 and the weight in kg. The second number is the normalization of the current performance with respect to the best possible performance. For instance, a norm of 2 for the shaded area indicates that the current shaded area is 2 times less than the largest possible shaded area. A norm of 2 for the weight indicated that the current weight is 2 times larger than the lowest possible weight. A norm of 1 indicates the best possible value has been achieved. The bars give a visual indication of the norm, the larger the bar the larger the value of the norm.

As you are designing you can save any design that you like or want to go back to by clicking on the save button located in the red area. You can visualize all the saved designs at once by double clicking on the capture button. This will save screenshots of the designs as they appear on the right hand side in the rhino design space. The screenshots will appear on this second screen saved as images with numbered file names. To make a saved design appear in the rhino design space you can change the slider to the desired design number and double click on Sift. For this please change the index number to be 1 smaller than the number shown in the screenshots. For instance, if you want to sift to design number 10 as shown in the screenshots then change the slider to 9 and double click on Sift.

Ask them if they have any questions. Ask if they have gained a sense for how the tool works.

*Give aesthetic preferences and task objectives sheet

MOO Instructions

Now we are adding an additional tool you can use called Multi-Objective Optimization (MOO) located in the purple area. This tool optimizes the designs based on the two objectives of shaded area and the weight. The tool does not take into account the overall appearance. MOO will explore 100 possible designs and will give you the top 20 designs. These 20 optimized designs are either the best in terms of shaded area, the best in terms of weight, or somewhere in between for both objectives.

To run the MOO tool, double click on MOO. The tool will take a couple of seconds to generate the designs.

Just as before, you can visualize all the optimized designs at once by double clicking on the capture button. This will save screenshots of the designs as they appear on the right hand side in the rhino design space. The screenshots will appear on this second screen saved as images with numbered file names. You can sift through those images to get a quick picture of the 20 optimized designs that were generated. To make an optimized design appear in the rhino design space you can change the slider to the desired design number and double click on Sift.

You can run the MOO tool multiple times, each time it will give a different set of 20 optimized designs. However, running it will overwrite any results generated earlier. Make sure you save any designs you like so you can go back to them. To run the MOO tool again, change the number of the design run in the yellow box. Make sure it is still in the format ".csv"

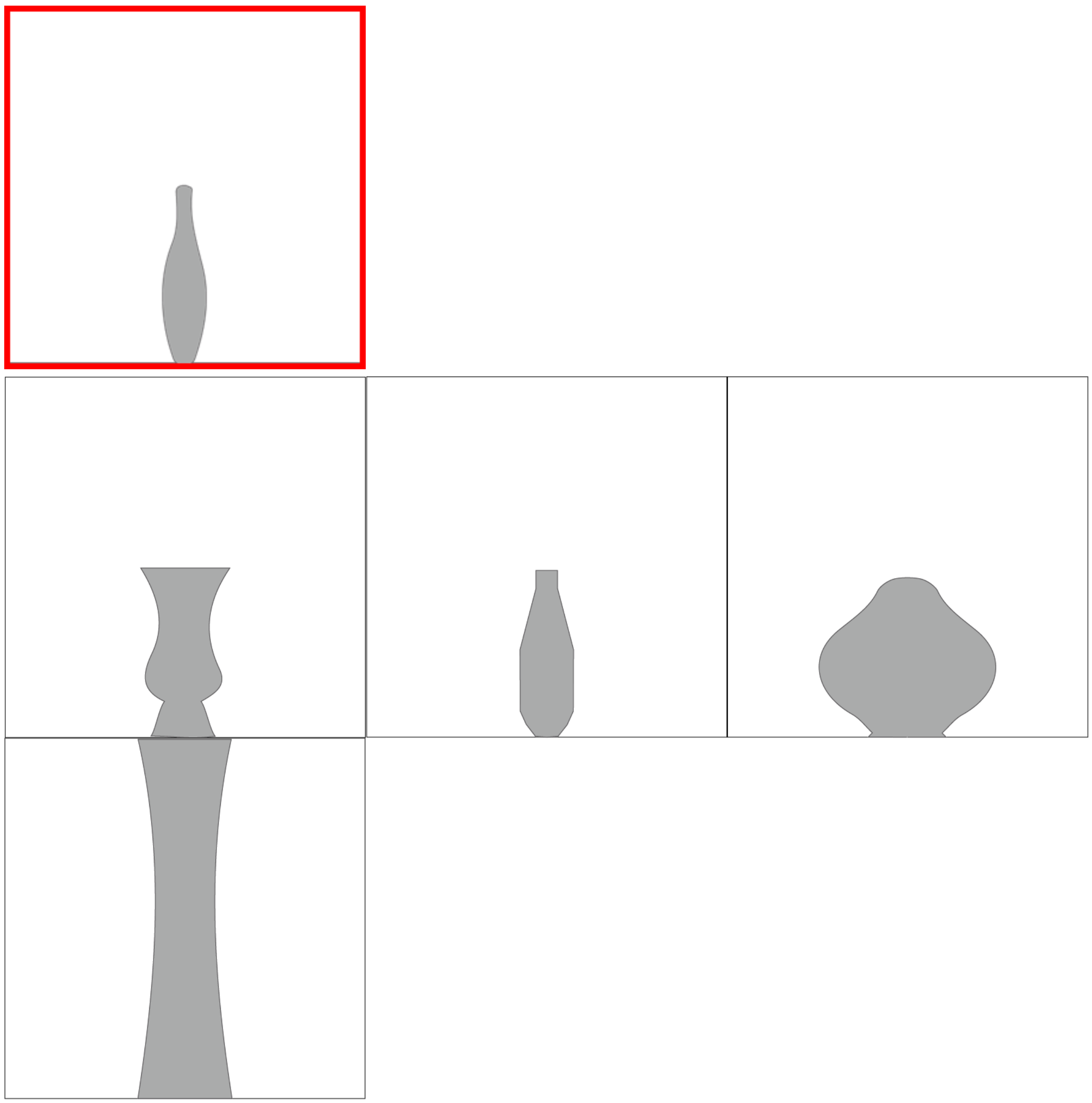
As before, your goal is to come up with as many canopy designs as you can for the cafe owner that meet the three objectives. You will have 15 minutes for this design task.

Appendix D Aesthetic Objective

Aesthetic Preferences - Version 1

The cafe owner expressed the need for the canopy to match the aesthetics of the cafe so that the aesthetics of the indoors and outdoors of the cafe are cohesive. To better understand the owner's preferences, we showed them a series of vase images that could be found in cafes. From the images we showed, the owner selected the one highlighted in red as their preferred vase.

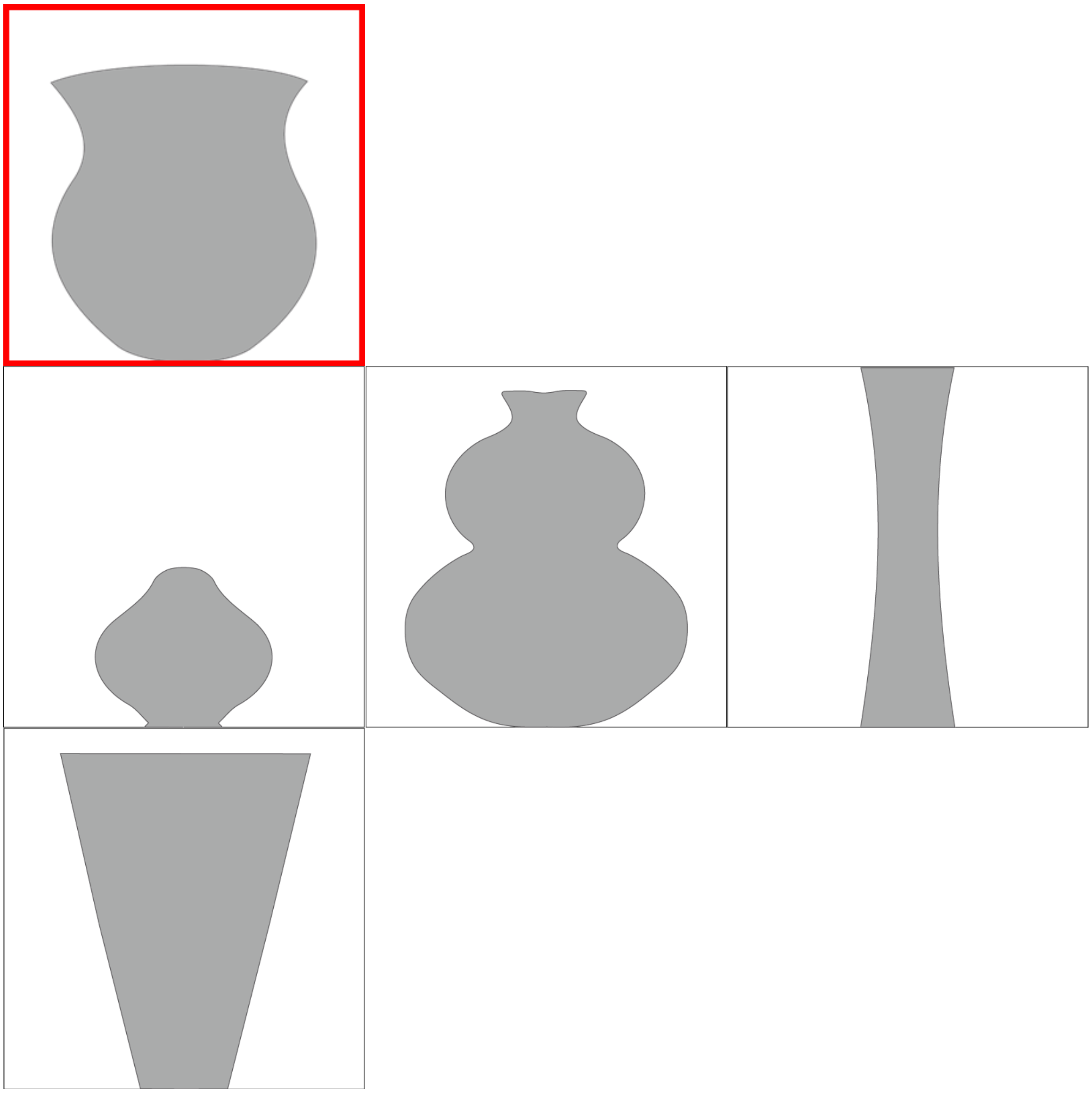
The owner described liking this vase because of its smaller size, more curved lines and simpler design that is appealing to the cafe aesthetic.



Aesthetic Preferences- Version 2

The cafe owner expressed the need for the canopy to match the aesthetics of the cafe so that the aesthetics of the indoors and outdoors of the cafe are cohesive. To better understand the owner's preferences, we showed them a series of vase images that could be found in cafes. From the images we showed, the owner selected the one highlighted in red as their preferred vase.

The owner described liking this vase because of its larger size, more curved lines and simpler design that is appealing to the cafe aesthetic.



Appendix E Design Tools Experiment Intake Survey

Start of Block: Default Question Block

Researchers Professor Maria Yang, Jana Saadi, Alessandro A Briseno-Tapia, and Zixuan Wu at The MIT Ideation Lab are conducting a study to better understand how designers use design tools powered by AI in the design process. We'd like to invite anyone with design experience to participate. Please complete this survey to determine your eligibility in the study. After you complete the survey, you will receive an email from us regarding the next steps.

Thank You!

Q1 Email (will only be used to send a follow-up email to schedule an experiment time)

____

Q2 What is your profession?

- ○ Student (1)
- ○ Faculty (2)
- ○ Industry (3)
- ○ Other (4) ____

Q3 What is your background?

- ◯ Mechanical Engineer (1)
- ◯ Architecture (2)
- ◯ Industrial Design (3)
- ◯ Computer Science (4)
- ◯ Aerospace Engineer (5)
- ◯ Other (Please Specify) (6) ____________________

Q4 How many years of experience do you have in design (this can include design related courses, internships, research, jobs)?

- ◯ None (1)
- ◯ Less than 1 year (2)
- ◯ 1-2 years (3)
- ◯ 2-3 years (4)
- ◯ More than 3 years (5)

Q5 Which design tools have you used? (select all that apply)

- ▢ Computer Aided Design Tools (1)
- ▢ Optimization Tools (2)
- ▢ Generative Design and AI Tools (3)
- ▢ Other (4)

End of Block: Default Question Block

Start of Block: Block 5

Q6 Please list the computer aided design tools you have used

____

Q7 How many years have you used these computer aided design tools?

- ○ Less than 1 year (1)
- ○ 1-2 years (2)
- ○ 2-3 years (3)
- ○ More than 3 years (4)

End of Block: Block 5

Start of Block: Block 6

Q8 Please list the optimization tools you have used

____

Q9 How many years have you used these optimization tools?

- ○ Less than 1 year (1)
- ○ 1-2 years (2)
- ○ 2-3 years (3)
- ○ More than 3 years (4)

End of Block: Block 6

Start of Block: Block 3

Q10 Please list the generative design and AI tools you have used

____

Q11 How many years have you used these generative design and AI tools?

- ○ Less than 1 year (1)
- ○ 1-2 years (2)
- ○ 2-3 years (3)
- ○ More than 3 years (4)

End of Block: Block 3

Start of Block: Block 2

Q12 Please list the other design tools you have used

____

Q13 How many years have you used these other design tools?

- ◯ Less than 1 year (1)
- ◯ 1-2 years (2)
- ◯ 2-3 years (3)
- ◯ More than 3 years (4)

End of Block: Block 2

Start of Block: Block 1

Q14 Age

- ◯ 18-21 (1)
- ◯ 22-25 (2)
- ◯ 26-36 (3)
- ◯ 37-47 (4)
- ◯ 48-60 (5)
- ◯ 60+ (6)

Q15 Gender

- ○ Male (1)
- ○ Female (2)
- ○ Non-binary / third gender (3)
- ○ Prefer not to say (4)
- ○ Prefer to self identify (5) ____

Q16 Are you a US Citizen or Green Card Holder?
This information will only be used while processing compensation for the experiment as per MIT guidelines (please see here for more information).

- ○ No (1)
- ○ Yes (2)

End of Block: Block 1

Appendix F End of Design Task Questionnaire

Start of Block: ID #

Identification

Insert Below Please Insert Participant ID #

____

Version #

○ 1

○ 2

○ 3

Which design task was just completed?

○ Task 1 (Free design)

○ Task 2 (MOO)

End of Block: ID #

Start of Block: Design Process

Design Process Questions

Q1 Can you describe your design process?

____

Q2 What are some of the things you were considering while designing?

____

Q3 Did you learn anything or have realizations at some point in the process?

____

End of Block: Design Process

Start of Block: Design Outcomes

Design Outcomes Questions

Q4 Of the designs you saved, which 3 would you like to show the cafe owner that best meets the three objectives, in ranked order?

	1 3 5 7 9 11 12 14 16 18 20
Design #1 (best)	
Design #2	
Design #3	

Q5 Why did you choose these designs?

____

End of Block: Design Outcomes

Start of Block: Satisfaction

1-5 scale; 5 is best In these designs, how satisfied are you with...

	Highly Dissatisfied	Somewhat Dissatisfied	Neutral	Somewhat Satisfied	Highly Satisfied
achieving the desired aesthetics?	○	○	○	○	○
achieving the desired shaded area?	○	○	○	○	○
achieving the desired weight?	○	○	○	○	○
balancing all three objectives?	○	○	○	○	○

End of Block: Satisfaction

Start of Block: Extra Notes

Notes / Extras

Notes Additional Comments:

____

End of Block: Extra Notes

Start of Block: User Design Preferences

Display This Question:

If Which design task was just completed? = Task 2 (MOO)

You will be shown several canopies, each visually different. You will be asked to group the canopies based on your knowledge of the **user's aesthetic preferences.** The order in which the canopies are placed in each group does not matter.

Please <u>do not</u> rank your preferences based on functionality, **focus only on the user's visual preference.**

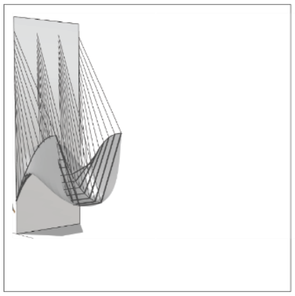
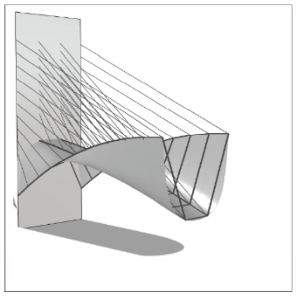
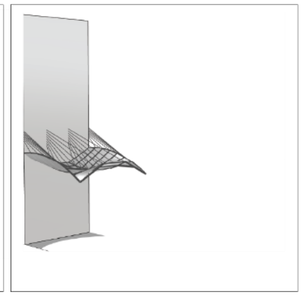
Display This Question:

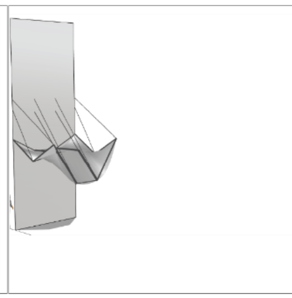
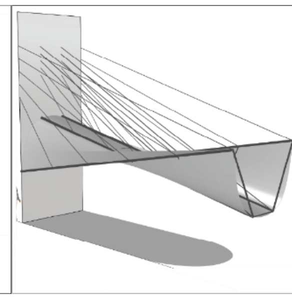
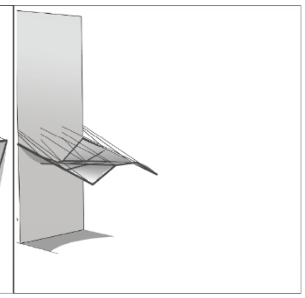
If Which design task was just completed? = Task 2 (MOO)

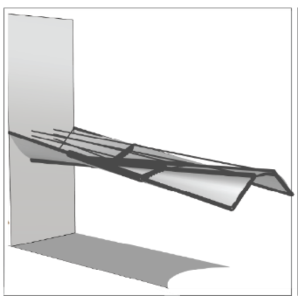
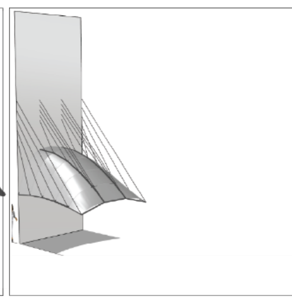
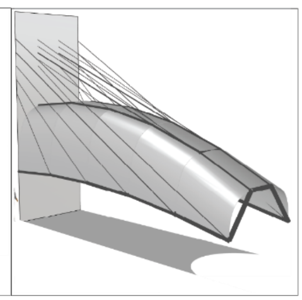
Sort each image of a canopy into one of 5 categories based on the **user's aesthetic preference**: Strongly Like, Somewhat Like, Neither Like nor Dislike, Somewhat Dislike, and Strongly Dislike.

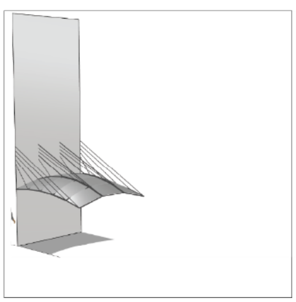
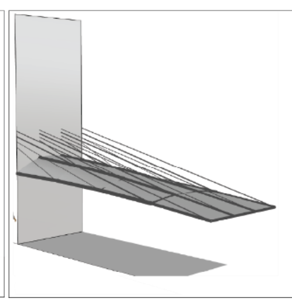
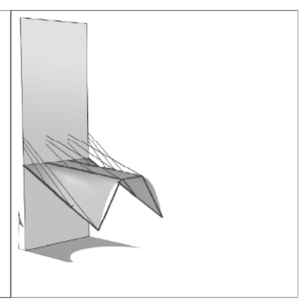
<u>Do not</u> rank preferences based on functionality, **focus only on visual preference.**

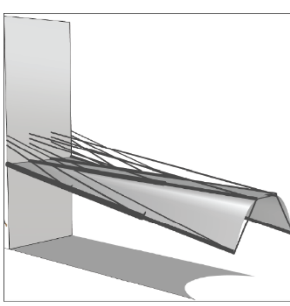
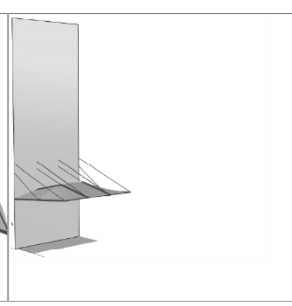
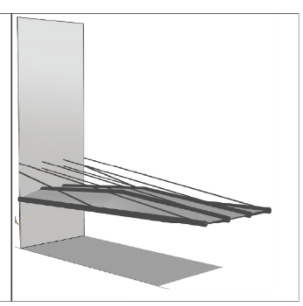
**CLICK ON IMAGE TO SEE FULL SIZE*

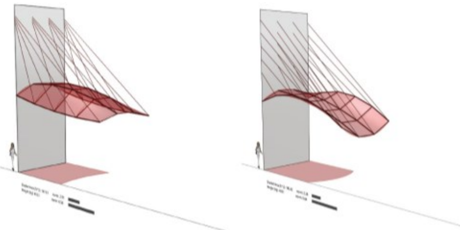
  

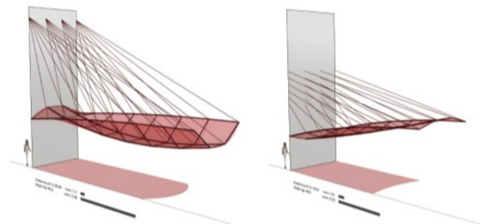
End of Block: User Design Preferences

Appendix G Rubric for Aesthetic Categorization

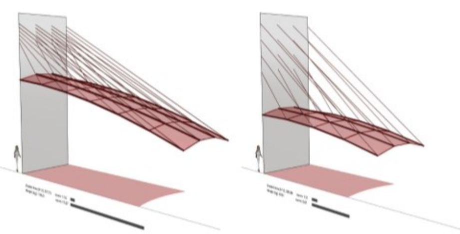
Simple
constant curvature, all concave or convex



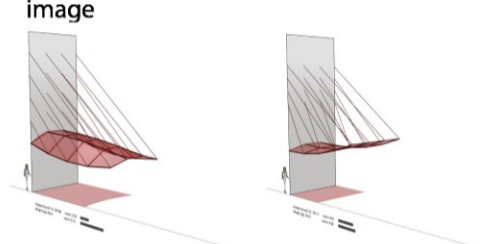
Complex
different curvatures



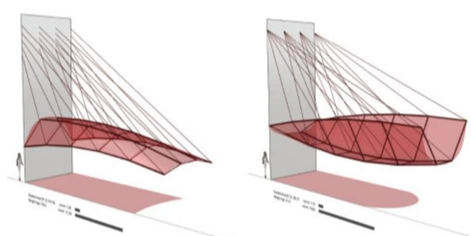
Long
the inner tip is beyond halfway of the image



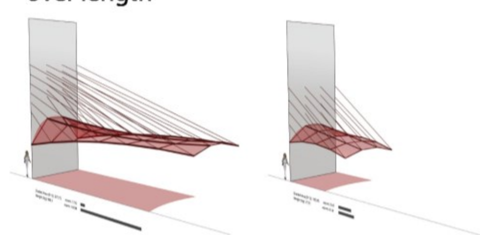
Short
the inner tip is shorter than the middle of the image



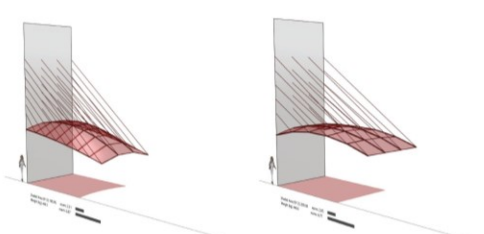
Wide
the widest part of the canopy is more than one person's height.



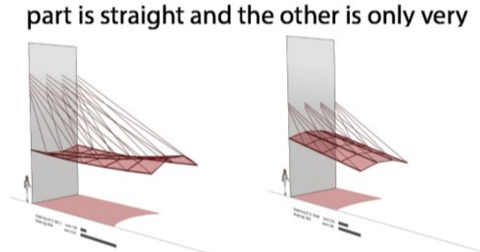
Narrow
the widest part of the canopy is less than one person's height and/or the canopy narrows over length



Curved
at least one segment has an obvious curve



Angular
Straight curvature along the length or one part is straight and the other is only very



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