OBSERVATIONS ON THE IMPLICATIONS OF GENERATIVE DESIGN TOOLS ON DESIGN PROCESS AND DESIGNER BEHAVIOUR

Saadi, Jana;
Yang, Maria

Massachusetts Institute of Technology

ABSTRACT

Developments in artificial intelligence (AI) are opening the possibilities for the development of more advanced design tools. An example of these innovations are generative design tools, in which the generation of complex and high performing products is possible. This study investigates the use of generative design tools and how they may influence the design process and designer behaviour. Six interviews of interdisciplinary designers were conducted to understand the implications of using generative design tools. It was observed that generative design tools primarily allow for quantitative inputs to the tool while qualitative metrics, such as aesthetics, are considered indirectly by designers. The subjectivity of the designer and how they incorporate the quantitative and qualitative metrics in the generative design tool can lead to differing outcomes between designers. Notable differences in tool usage are also observed between expert and novice computational designers. Additional studies should be conducted to further understand the extent generative design tools impact the design process, designer behaviour, and design outcomes.

Keywords: Design process, Artificial intelligence, Generative Design, Human behaviour in design, Design Tools

Contact:
Saadi, Jana
Massachusetts Institute of Technology
United States of America
jsaadi@mit.edu

Cite this article: Saadi, J., Yang, M. (2023) 'Observations on the Implications of Generative Design Tools on Design Process and Designer Behaviour', in *Proceedings of the International Conference on Engineering Design (ICED23),* Bordeaux, France, 24-28 July 2023. DOI:10.1017/pds.2023.281

1 INTRODUCTION

Developments in artificial intelligence (AI) have opened the way for more sophisticated tools for design. Generative design tools are a category of such tools that has grown in use in both industry and research. Generative tools rely on algorithms to create designs based on designer-defined specifications (Buonamici et al., 2020; Caetano et al., 2020; Cui and Tang, 2017; Noor, 2017). Generative design tools are noted for their ability to output a large number of designs relatively quickly and result in geometries far more complex than could be created by a human designer.

Generative design has the potential to also influence other factors, such as improved user satisfaction or reduced environmental footprint of products (Cui and Tang, 2017; Gascón Alvarez et al., 2022). Research and industry projects provide examples where generative design tools can be used to create high-performing products with wide-reaching impacts. For instance, Airbus used Fusion 360 Generative Design to redesign an Airbus A320 airplane cabin partition. Using a generative design algorithm based on growth patterns found in nature, they designed a partition with a lattice optimized to be both strong and lightweight. The design is 45% lighter than the original partition and yet 8% stronger. This significant savings in weight has the potential to decrease the Airbus A320's fuel consumption and cut its CO_2 emissions by up to 166 metric tons per aircraft each year ("Generative Design at Airbus | Customer Stories | Autodesk"). This illustrates the potential for generative design, in which the abilities of human designers can be augmented by AI to produce high performing results with substantial impacts. At the same time, the influence of these computational tools on designers, their behaviors, and the product design process needs to be more thoroughly understood. This research project aims to provide key insights about the implications of using generative design tools in the design process.

RQ: What are some of the implications of generative design tools on the design process?

Previous research has shown that computational tools in design can affect aspects of human designer behaviors, such as communication between designers in design teams and confidence of designers at different stages of the design process (Song et al., 2020; Zhang et al., 2021). Similarly, the approach of human designers using the computational tools can affect the tool's performance. For instance, qualitative design metrics, such as aesthetics, cannot easily be defined in many generative design tools. Therefore, designers may alter the tool inputs and outputs to influence the aesthetics. This subjective behavior can lead to different design outcomes and can even differ between designers (Krish, 2011).

This study interviews designers about their use of generative design tools in their design processes and uses a grounded theory approach to analyze the data collected. Commercially available generative design tools created by commonly used modelling software companies including Autodesk Fusion 360, NTopology, CATIA, and Rhinoceros are used. This study builds on previous research by the authors to develop an understanding of the generative design process (Saadi and Yang, 2023).

2 BACKGROUND

2.1 Generative design

Generative design tools can augment human designers throughout the design process to create numerous designs that are often more advanced than what can be created by humans and AI independently. An example of a range of designs optimized for designer defined objectives created using generative design tools is shown in Figure 1. While generative design tools can lead to more creative geometries yielding higher performing products, their use in the design has the potential to drastically change a designer's approach to the design process (Cui and Tang, 2017).

Generative design tools have been increasing in use in research and industry. Buonamici et al. (2020) compared designs of a robot gripper arm made in Autodesk Fusion 360 Generative Design with those made using more traditional topology optimization tools. The designs created by both computational tools yielded similarly performing parts, indicating the potential of newer generative design tools to be incorporated in the design process.

https://doi.org/10.1017/pds.2023.281 Published online by Cambridge University Press

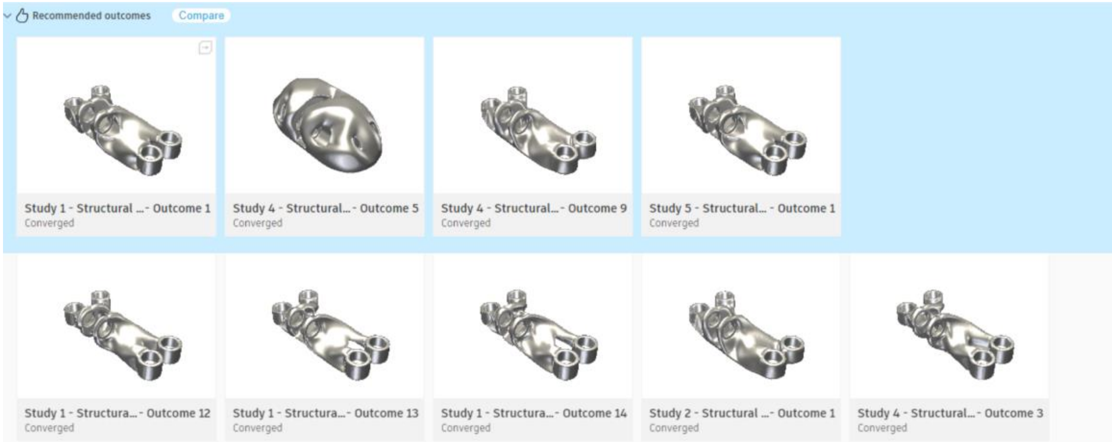

Figure 1 Generative design outputs of a GE bracket optimized for weight created using Autodesk Fusion 360 generative design.

Generative design tools have more recently been shown to also be useful in early design process stages. Sketches developed by deep learning generative design tools have been found to be functionally comparable to simple line sketches created by human designers and therefore have the potential to aid designers in brainstorming and ideation (Lopez et al., 2018). Research on the application of generative design and topology optimization tools in early stage design in an industrial case indicates designers adopt a different way of thinking to define the design space (Vlah et al., 2020). Computational tools have also been used to develop parametric models to generate designs with desired shape grammars, defining the aesthetics of the product in early stages of development (Alcaide-Marzal et al., 2020).

2.2 Designer behavior in generative design

Computational tools can affect designers by influencing their cognitive processes and their design processes which can impact the designs generated (Song et al., 2020). Therefore, it is important to further investigate the influence generative design tools have on human designers and vice versa. Generative design tools require specific conditions and inputs to generate designs. These are often different from what is required in the early stages of traditional design process and can therefore require designers to adopt different design practices to use the generative design tools (Vlah et al., 2020). This can be compounded by the complex realities of design projects, in which design parameters defined early on in the process change due to aesthetic preferences, functional requirements, or financial considerations established later on in the process (Holzer et al., 2007). Therefore, designers must learn to adapt their way of thinking not only to incorporate generative design tools in the process, but also to accommodate changing requirements throughout the design process.

Incorporating computational design tools in the design process has been shown to effect designers. Bansal et al. (2019) found that while updates to an AI tool can grant it higher accuracy, the changes to the tool's functionality disrupts the designer's mental model of the tool and can decrease a design team's performance. Gyory et al. (2021) investigated the communication structures of human-AI. They found that incorporating AI into design teams leads to higher level of communication between designers as well as greater diversity, relevance, and cohesion in the information passed between designers.

While generative design tools may affect designers, the designers' behaviors and how they use the tool may also influence the design process and design outcomes. Zhang et al. (2021) investigated AI assisted design teams and the impact of abrupt problem changes have on team performance. They found that AI tools can provide suggestions that can boost the performance of initially low-performing teams, but the performance of high-performing teams using AI is decreased. This can be due to the designers' increased cognitive load to evaluate and incorporate the AI tool suggestions and the designers' incorrect interpretation of the AI suggestions. Pillai et al. (2020) used in lab experiments to study the effects of the design of computational tools on early-stage design exploration. They found that the design of computational tools and how designers interact with it can affect the designer's behavior and the resulting design outcome.

https://doi.org/10.1017/pds.2023.281 Published online by Cambridge University Press

Current research indicates that computational tools can have varying impacts on human design teams and design outcomes depending on its effect on designer behaviors. However, more research is required to investigate the influence of generative design tools on individual designer behaviors (Gyory et al., 2021). As such, this study seeks to understand how integrating generative design tools within design processes can affect the designer behavior and design process.

3 METHODS

This study applies a grounded theory approach, a method from qualitative research practices to build new theories grounded in collected data (Friedman, 2003; Li and Seering, 2019). This methodology allowed for a descriptive understanding of the implications of generative design tools on designer behavior and design process through semi-structured interviews of six designers using generative design tools in their interdisciplinary work.

3.1 Interviews

Six designers in architecture, industrial design, and mechanical engineering were interviewed regarding their use of generative design tools. Semi-structured interviews were conducted to capture both breadth and depth of topics based on the experience of the interviewee (Creswell et al., 2003). The interview spanned several topics including the designers' process stages, their influence in the process, and the process characteristics. This data and analysis in this study focus on the latter two themes to understand how the design process is influenced by designers and generative design tools. The interviewees were graduate students or industry designers who regularly use generative design tools in their projects. The types of tools used by the designers and their level of experience using their respective tool are shown in Table 1. The types of products produced by the designers using these tools included a robot chassis, automobile components, small brackets, furniture, art installations, and large building structures. Interviewees were first recruited through the research groups' networks. This was followed by a snowball sampling technique in which additional recruits were referred to by the interviewees. The interviews averaged about an hour long and were conducted in person or virtual. The interviews were audio and screen recorded. Although only six designers were interviewed in this study, the overall design process described by the interviewees remained consistent.

Table 1: Background, generative design tool, and experience level 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)

3.2 Transcription and coding

Transcriptions were generated from audio recordings using an automatic software (otter.ai) and edited manually by the researchers. The transcriptions were then imported into a qualitative analysis software (ATLAS.ti). The interviews were reviewed and coded by the researcher that conducted the interviews to ensure familiarity and understanding of the themes discussed (Thomas, 2006). The interviews were coded for themes through several stages (Figure 2). First a descriptive open coding scheme was used, preliminarily categorizing the data passages with descriptions that summarized the meaning of important statements (Crang and Cook, 2007; Saldana, 2015). This process allowed the themes to be developed directly from the interviews and not be influenced by an outside set of themes (Charmaz, 2008; Crang and Cook, 2007). This was followed by axial coding in the second stage to organize the codes into themes, combining similar descriptive codes into broader categories (Saldana, 2015). For

https://doi.org/10.1017/pds.2023.281 Published online by Cambridge University Press

instance, “cool looking” designs and “organic looking” designs were coded separately at level 1, and then combined at level 2 into one category of “preferred aesthetic”. This was a subcategory of “Aesthetics”, which also included the level 2 category of “Aesthetic may not matter”. Finally, theoretical coding was used to thematize the simplified categories into broader subcategories and respective themes (Lauff et al., 2018; Saldana, 2015). The subcategory of “Aesthetics” was grouped under the theme of “Subjective Metrics” developed in the theoretical level of coding.

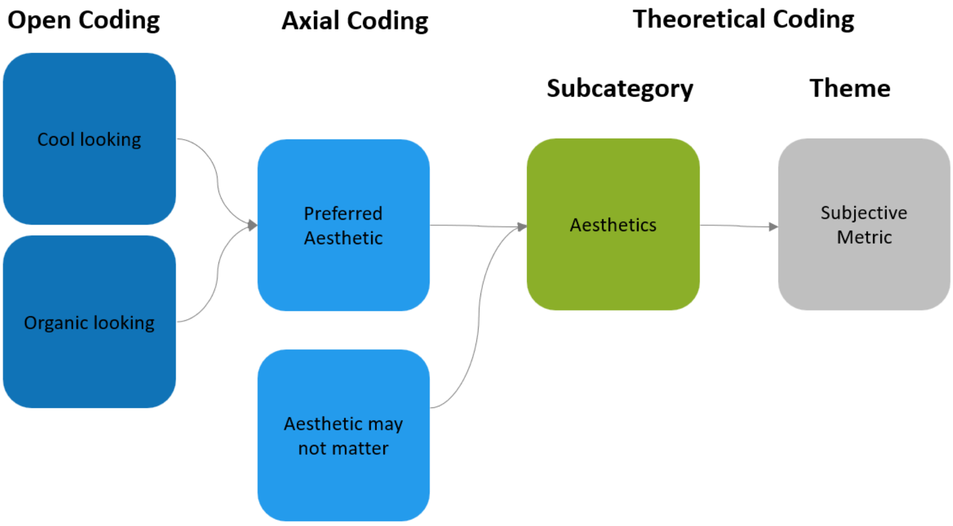

Figure 2: The three stages of coding used: open coding, axial coding, and theoretical coding. Examples of categories from the data under the theme of “Aesthetics” are shown.

The three stages of coding were iterated on until no additional categories were created. This multi-level coding process ensured that the interviews were used to develop themes unbiased by external models and expectations (Charmaz, 2008; Thomas, 2006). Some of the interviewees, computational tool experts, and qualitative research methods specialists were consulted to validate the findings through the qualitative analysis (Saldana, 2015).

4 RESULTS

An understanding of the designers' processes using the generative design is derived from the interviews. This is useful to begin to understand the areas that 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 it is approached by designers.

4.1 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

https://doi.org/10.1017/pds.2023.281 Published online by Cambridge University Press

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 (Lo, 2018). 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 (Alcaide-Marzal et al., 2020; Oh et al., 2019; Yümer et al., 2015).

4.2 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 (Krish, 2011). 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."

4.3 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.

4.4 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 (Ulrich et al., 2019). The modular designs created can more easily be used for future variations of the design (Simpson et al., 2014). 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.

4.5 Design time

Using generative design tools has the potential to change the amount of time spent in each stage of the design process and possible 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

https://doi.org/10.1017/pds.2023.281 Published online by Cambridge University Press

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 spend defining and iterating the design problem and modifying the designs may end up negating any time saved generating designs using the tool.

5 DISCUSSION

A generative design process provides the opportunity for designers and computational tools to interact in design to generate high performing products. Using generative tools in design affects the design process, designer behavior, and design outcomes, as illustrated through six interviews conducted of designers using generative design tools. The performance-driven commercial generative design tools bring about a quantitative-based problem definition to identify objective, parameter, and constraint inputs into the generative design tool. The rapid and iterative generation of multiple designs based on the tool inputs can shorten the design process time and front load many of the design decisions such as material selection and manufacturing method. It can also make the process more flexible, allowing quick changes to the tool inputs to generate a different set of designs.

However, 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 ("GE Jet Engine Bracket Challenge | Engineering & Design Challenges | GrabCAD" 2013). 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 (Whalen, Beyene, and Mueller 2021). However, depending on the path each designer chooses to take and their choice of workarounds, the 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.

6 CONCLUSIONS AND FUTURE WORK

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 did not allow for an understanding of the nuanced differences that may exist between different generative design tools or between disciplines of design. Future work can incorporate more interviews to explore the breadth of generative design tools their influence on design process and the design outcomes.

https://doi.org/10.1017/pds.2023.281 Published online by Cambridge University Press

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 design process of novice and expert computational designers was the same. Future experimentation can be used to determine whether the outcome of the process is comparable between novices and experts to explore whether the generative design process flattens the difference between novices and experts.

ACKNOWLEDGMENTS

This research was supported in part by the National Science Foundation Award #1854833 and in part by the NewSat project. The NewSat project is co-funded by the Operational Program for Competitiveness and Internationalisation (COMPETE2020), Portugal 2020, the European Regional Development Fund (ERDF), and the Portuguese Foundation for Science and Technology (FTC) under the MIT Portugal program. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the funders.

REFERENCES

Alcaide-Marzal, J., Diego-Mas, J.A. and Acosta-Zazueta, G. (2020), "A 3D Shape Generative Method for Aesthetic Product Design", Design Studies, Vol. 66, pp. 144–176, https://dx.doi.org/10.1016/j.destud.2019.11.003.

Bansal, G., Nushi, B., Kamar, E., Weld, D.S., Lasecki, W.S. and Horvitz, E. (2019), "Updates in Human-AI Teams: Understanding and Addressing the Performance/Compatibility Tradeoff", Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 33 No. 01, pp. 2429–2437, https://dx.doi.org/10.1609/aaai.v33i01.33012429.

Buonamici, F., Carfagni, M., Furferi, R., Volpe, Y. and Governi, L. (2020), "Generative Design: An Explorative Study", Computer-Aided Design and Applications, Vol. 18, pp. 144–155, https://dx.doi.org/10.14733/cadaps.2021.144-155.

Caetano, I., Santos, L. and Leitão, A. (2020), "Computational design in architecture: Defining parametric, generative, and algorithmic design", Frontiers of Architectural Research, Vol. 9 No. 2, pp. 287–300, https://dx.doi.org/10.1016/j.foar.2019.12.008.

Charmaz, K. (2008), "Grounded Theory as an Emergent Method", Handbook of Emergent Methods, The Guilford Press, New York, NY, US, pp. 155–170.

Crang, M. and Cook, I. (2007), Doing Ethnographies, SAGE Publications Ltd, London.

Creswell, J., Clark, V., Gutmann, M. and Hanson, W. (2003), "Advance Mixed methods Research Designs", Handbook of Mixed Methods in Social and Behavioral Research, pp. 209–240.

Cui, J. and Tang, M. (2017), "Towards Generative Systems for Supporting Product Design", International Journal of Design Engineering, Vol. 7, p. 1, https://dx.doi.org/10.1504/IJDE.2017.085639.

Friedman, K. (2003), "Theory Construction in Design Research: Criteria: Approaches, and Methods", Design Studies, Vol. 24 No. 6, pp. 507–522, https://dx.doi.org/10.1016/S0142-694X(03)00039-5.

Gascón Alvarez, E., Stamler, N.L., Mueller, C.T. and Norford, L.K. (2022), "Shape optimization of chilled concrete ceilings – Reduced embodied carbon and enhanced operational performance", Building and Environment, Vol. 221, p. 109330, https://dx.doi.org/10.1016/j.buildenv.2022.109330.

"Generative Design at Airbus | Customer Stories | Autodesk". (n.d.). , available at: https://www.autodesk.com/customer-stories/airbus (accessed 14 November 2022).

Gyory, J.T., Song, B., Cagan, J. and McComb, C. (2021), "Communication in AI-Assisted Teams During an Interdisciplinary Drone Design Problem", Proceedings of the Design Society, Cambridge University Press, Vol. 1, pp. 651–660, https://dx.doi.org/10.1017/pds.2021.65.

Holzer, D., Dominik, Hough, Richard, Burry, M., and Mark. (2007), "Parametric Design and Structural Optimisation for Early Design Exploration", International Journal of Architectural Computing Vol. 5 - No. 4, Pp. 625-643, Vol. 5, https://dx.doi.org/10.1260/147807707783600780.

Krish, S. (2011), “A Practical Generative Design Method”, Computer-Aided Design, Vol. 43 No. 1, pp. 88–100, https://dx.doi.org/10.1016/j.cad.2010.09.009.
Lauff, C., Kotys-Schwartz, D. and Rentschler, M. (2018), “What is a Prototype? What are the Roles of Prototypes in Companies?”, Journal of Mechanical Design, Vol. 140, https://dx.doi.org/10.1115/1.4039340.
Li, Z. and Seering, W. (2019), “Build Your Firm With Strangers?: Longitudinal Studies on Open Source Hardware Firm Growth”, Proceedings of the ASME 2019 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, presented at the ASME 2019 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, Anaheim CA, USA, https://dx.doi.org/10.1115/DETC2019-97618.
Lo, C.-H. (2018), “Application of Aesthetic Principles to the Study of Consumer Preference Models for Vase Forms”, Applied Sciences, Multidisciplinary Digital Publishing Institute, Vol. 8 No. 7, p. 1199, https://dx.doi.org/10.3390/app8071199.
Lopez, C.E., Miller, S.R. and Tucker, C.S. (2018), “Exploring Biases Between Human and Machine Generated Designs”, Journal of Mechanical Design, Vol. 141 No. 2, https://dx.doi.org/10.1115/1.4041857.
Noor, A.K. (2017), “AI and the Future of the Machine Design”, Mechanical Engineering, Vol. 139 No. 10, pp. 38–43, https://dx.doi.org/10.1115/1.2017-Oct-2.
Oh, S., Jung, Y., Kim, S., Lee, I. and Kang, N. (2019), “Deep Generative Design: Integration of Topology Optimization and Generative Models”, Journal of Mechanical Design, Vol. 141 No. 11, https://dx.doi.org/10.1115/1.4044229.
Pillai, P.P., Burnell, E., Wang, X. and Yang, M.C. (2020), “Effects of Robust Convex Optimization on Early-Stage Design Space Exploratory Behavior”, Journal of Mechanical Design, Vol. 142 No. 12, https://dx.doi.org/10.1115/1.4048580.
Saadi, J.I. and Yang, M.C. (2023), “Generative Design: Reframing the Role of the Designer in Early-Stage Design Process”, Journal of Mechanical Design, Vol. 145 No. 4, https://dx.doi.org/10.1115/1.4056799.
Saldana, J. (2015), The Coding Manual for Qualitative Researchers, 3rd ed., SAGE Publications Ltd.
Simpson, T.W., Jiao, J. (Roger), Siddique, Z. and Hölttä-Otto, K. (2014), Advances in Product Family and Product Platform Design: Methods & Applications, 1st ed., Springer New York, NY.
Song, B., Soria Zurita, N., Zhang, G., Stump, G., Balon, C., Miller, S., Yukish, M., et al. (2020), “Toward Hybrid Teams: A Platform to Understand Human-computer Collaboration during the Design of Complex Engineered Systems”, Proceedings of the Design Society: DESIGN Conference, Vol. 1, presented at the International Design Conferenece, pp. 1551–1560, https://dx.doi.org/10.1017/dsd.2020.68.
Thomas, D.R. (2006), “A General Inductive Approach for Analyzing Qualitative Evaluation Data”, American Journal of Evaluation, Vol. 27 No. 2, pp. 237–246, https://dx.doi.org/10.1177/1098214005283748.
Ulrich, K.T., Eppinger, S.D. and Yang, M.C. (2019), Product Design and Development, McGraw Hill Education.
Vlah, D., Žavbi, R. and Vukašinović, N. (2020), “Evaluation of Topology Optimization and Generative Design Tools as Support for Conceptual Design”, Proceedings of the Design Society: DESIGN Conference, Cambridge University Press, Vol. 1, pp. 451–460, https://dx.doi.org/10.1017/dsd.2020.165.
Yümer, M.E., Chaudhuri, S., Hodgins, J. and Kara, L. (2015), “Semantic Shape Editing Using Deformation Handles”, ACM Trans. Graph., Vol. 34 No. 4, p. 12, https://dx.doi.org/10.1145/2766908.
Zhang, G., Raina, A., Cagan, J. and McComb, C. (2021), “A Cautionary Tale about the Impact of AI on Human Design Teams”, Design Studies, Vol. 72, p. 100990, https://dx.doi.org/10.1016/j.destud.2021.100990.