ISSN: 2230-9926

Available online at http://www.journalijdr.com

IJDR

International Journal of Development Research
Vol. 11, Issue, 03, pp. 45148-45152, March, 2021
https://doi.org/10.37118/ijdr.20747.03.2021

RESEARCH ARTICLE OPEN ACCESS

EVALUATING USABILITY OF GENERATIVE DESIGN PROCESS FOR HUMAN-CENTERED DESIGN

***Michael Botyarov and Dr. Erika Miller**

Department of Systems Engineering, Colorado State University, Fort Collins, CO 80523 USA

ARTICLE INFO

Article History:
Received 19th December, 2020
Received in revised form
22nd January, 2021
Accepted 29th February, 2021
Published online 17th March, 2021

Key Words:

Generative design, Output, Optimization, Autodesk, Cognition, Human factors.

****Corresponding author:* *Michael Botyarov***

ABSTRACT

Generative design tools extend solution spaces for designers, however there is likely a limit to the usefulness of a broad set of design outputs from a human factors perspective. This study evaluates generative design tool output from the human factors perspective. A usability study was performed with 28 participants, where participants evaluated design solutions in Autodesk Fusion 360 and then answered survey questions about their perception of the output the tool provided. Participants were asked to evaluate the design solution quality, design solution quantity, breadth of the solution envelope, and efficiency of design filters. Analysis of survey data indicated that although generative design has useful applications within the systems engineering life cycle, there is a need to enhance existing toolsets for parsing generative design solutions (e.g. design filters, limited design space, etc.). The development of parsing elements would reduce human cognitive workload for the designer, thereby optimizing the generative design process.

Citation: ***Michael Botyarov and Dr. Erika Miller,*** **2021.** "Evaluating usability of generative design process for human-centered design", *International Journal of Development Research*, 11, (03), 45148-45152.

INTRODUCTION

The systems engineering life cycle provides a structured framework of dealing with the complexity that arises from increasingly integrated systems, comprising multiple subsystems and myriad components. The system engineering life cycle consists of multiple phases, including (1) conceptual design, (2) preliminary design, (3) detail design and development, (4) production, and (5) operational use and system support phases, after which system retirement occurs (Blanchard, 2004). The primary activities of the conceptual design phase include needs identification, requirements analysis, selection of feasible technology application, selection of technical approach, and functional definition of the system (Blanchard, 2004). These activities correlate to parallel engineering efforts focused on the creation of system alternatives, a subset of which can be refined in the upcoming systems engineering life cycle phases. Generative design operates at the conceptual phase of design, where the design is still under formulation (Krish, 2011). Generative design exists to facilitate the design process by providing novel solutions to complex problems that designers may have otherwise been inefficient in solving or even unable to solve (McKnight, 2017). Generative design tools have been developed to ingest the problem definition as input to produce feasible solutions for the given problem (Kazi, 2017). Due to the inherently ambiguous nature of the conceptual design phase, generative design inputs can be directly derived from system requirements (e.g. manufacturing process, weight, material type, etc.). In cases where the problem is abstract or novel, such that the designer does not have a clear starting point, leveraging generative design will enable the designer to explore the extent of the design envelope by analyzing a greater quantity of design possibilities when compared to traditional modeling processes (Kazi, 2017).

Generative Design Tools: The majority of generative design tools are computer-aided design (CAD) based. Commercially available generative design tools include Altair's OptiStruct and solidThinking, Autodesk's Nastran Shape Generator, and Siemen's Frustum (Kazi, 2017). These design tools have the ability to create thousands of design options in substantially less time than the traditional development lifecycle (McKnight, 2017). Therefore, a CAD tool (Autodesk Fusion 360), as described in the following section, will be used in this study.

Autodesk Fusion 360: Autodesk Fusion 360 is a CAD tool that integrates the entire product design and development process in a single tool (Song, 2018). A key feature of Autodesk Fusion 360 is the ability to leverage cloud computing to identify a solution set for a generative design solution. The generative design workflow using Autodesk Fusion 360 consists of (1) opening an existing model or creating a new model workspace to serve as the basis for the generative design study, (2) optionally modifying the generative model (e.g. if existing model, can create bodies to represent preserve, obstacle, and starting shape geometries in a design problem (e.g. genotype)), (3) setting up a design problem and specify requirements, (4) generating outcomes that satisfy requirements, and (5) exploring outcomes using tools to help identify the optimal outcome. Given these capabilities, Autodesk Fusion 360 will be used as the generative design tool in this study.

Designer Cognition & Generative Design Output: Generative design systems attempt to enhance the creativity of the designer by exploring search spaces in an innovative and efficient way to produce novel solutions (Bentley, 2002). The automatic permutation of large quantities of design alternatives can inspire ideas and concepts, which the designer would not necessarily have considered without the support of a generative design tool (Fischer, 2001). The designer is a crucial actor in the generative design process since the designer ultimately evaluates generative design tool output to select an alternative which to proceed to the next phase of the systems engineering life cycle. However, downselecting to a single design alternative is arduous since the generative design process often produces thousands of design alternatives (Krish, 2011). The magnitude of available alternatives subsequently places a significant cognitive workload on the designer (Krish, 2011). Due to the limitations of human cognitive ability, the designer is only able to evaluate a limited number of design solutions without cognitive fatigue (Bentley, 2002). Therefore, this study will serve to evaluate the designer's perceived level of satisfaction with current generative design output (e.g. design alternatives) from Autodesk Fusion 360. Based on the results of this study, it will be determined if and how the quantity of generative design tool output needs to be reduced, while maintaining novel solution integrity, such that cognitive workload is reduced while simultaneously increasing overall satisfaction with the generative design process.

Related Works: The purpose of CAD tools is to facilitate the design process and in the case of generative design tools, to enhance human creativity by producing a set of novel solutions. The objective of this study is to determine how to improve generative design output (e.g. quantity of design alternatives), therefore factors that influence design selection must be considered to understand how a human would evaluate generative design output. The following sections discuss factors that contribute to design evaluation (e.g. design aesthetics (human emotion), design selection criteria (human-in-the-loop), and design optimization (minimal human involvement) evaluation).

Design Aesthetics: Previous literature has indicated that in addition to design characteristics (e.g. material, load bearing capability, etc.), design aesthetics are a primary contributor to design (or product) selection (Helander, 2008). In an experiment regarding chair design, chair users were able to make consistent and informative judgments regarding chair aesthetics (Helander, 2008). However, the users had difficulties in distinguishing between chairs of different ergonomics quality (e.g. design characteristics) because ergonomics differences were too subtle to be perceived, and therefore virtually indistinguishable (Helander, 2008). It becomes evident that when a human performs design selection, there are more factors involved than solely design characteristics. Namely, design aesthetics, which are strongly correlated with human emotion are leveraged in the design selection process (Helander, 2003). Further research into design aesthetics will help determine (1) how to use scientific methods to study aesthetics concepts, and (2) how to incorporate scientific methods in the aesthetic design and evaluation process (Helander, 2003).

Design Selection Criteria: Design selection criteria are factors that aid the human in selecting a design alternative. Since generative design systems are beneficial primarily during the conceptual design phase, common design selection criteria include technical performance measures (TPMs), which serve as a method to evaluate alternatives by comparing quantitative values describing system performance (e.g. availability, failure rate, etc.) for each alternative (Blanchard, 2004). Additional design selection criteria deal with aspects of the design outside of performance requirements, including cost, schedule (e.g. time to market, etc.), procurement (e.g. supplier involvement), and quality (Blanchard, 2004). In order to identify TPMs, and other design selection criteria, stakeholders gather to discuss the functional baseline of the system. Once identified, design selection criteria are assigned weightings based on their perceived level of importance. The set of design alternatives is then evaluated against these criteria to select one to move forward with in the systems engineering life cycle (Blanchard, 2004). Unlike design aesthetics, which rely heavily on the human to evaluate a design based off appearance, design selection criteria provide a structured approach to design evaluation that includes a mixture of human involvement (e.g. criteria identification, weighting assignment, etc.) and automation (e.g. rating designs based on defined criteria). The two subsequent sections discuss just noticeable difference and paradox of choice, both of which can influence the human element in the design selection criteria process.

Just Noticeable Difference: Humans have sensory thresholds, which are defined as the amount of a stimulus above which an experience will be noticed (Garneau, 2013). These thresholds are categorized into absolute thresholds and difference thresholds (Garneau, 2013). The absolute threshold is defined as the smallest amount of stimulus energy necessary to produce a sensation, whereas the difference threshold is defined as the change in stimulus required to produce a just noticeable difference in the sensation (Garneau, 2013). These thresholds can be attributed to design since the evaluation of a design involves human cognition (e.g. visual stimuli). Methods of evaluation of sensory thresholds all involve presenting participants with a variety of stimuli and asking the participant to identify which stimuli, or difference between stimuli (e.g. just noticeable difference), are perceptible (Garneau, 2011). Incorporating just noticeable difference into the design process will correlate to a decrease in required design variation (Garneau, 2013). This may subsequently result in an increase in human satisfaction and design process efficiency.

Paradox of Choice: The traditional definition of the paradox of choice is a phenomenon in which the result of too many choices leaves the human less happy, less satisfied, and occasionally paralyzed (Piasecki, 2011). However, an expanded definition of the paradox of choice yields that lack of meaningful choice, rather than an overwhelming amount of choice, that leaves the human less happy, less satisfied, and occasionally paralyzed (Piasecki, 2011). To further complicate the decision process, humans themselves are often unable to explicitly define what constitutes a meaningful choice (Piasecki, 2011). In the context of generative design, this further implies that generative design system output needs to be optimized such that not only a limited subset of design options is presented, but that the design options themselves are dissimilar. Empirical studies have examined the specific effects of choice-set size on the decision behavior of humans, suggesting that the presence of additional options may hamper the ability to identify the option that best matches requirements, thereby reducing the likelihood a decision would be made (Kida, 2010). With a large quantity of options presented, humans may experience a higher level of anticipated regret associated with the many alternatives that will not be chosen, particularly those that may be more optimal, since they may feel personally responsible if a perfect selection is not made due to the multitude of available alternatives (Kida, 2010). It is important to note the role experience plays in choice selection and that a human with more experience in the area may prefer to have more options (Kida, 2010). In the context of generative design, this may imply that there is a lower control limit to the quantity of design alternatives that should be presented, meaning the output should not be so constrained that only a few options are presented.

Design Optimization: In order to limit the impact of human emotion on the design process (e.g. design aesthetics or development of design evaluation criteria), unique systems have been developed for design optimization that automate the development of a single, optimized alternative. A popular method for design optimization is topology optimization, which is an automated method of design exploration, primarily used during late stages of the design process (e.g. detailed design phase of systems engineering life cycle) (2). Since important aspects of the design are already established, topology optimization focuses on operations within narrow bounds to improve specific performance (e.g. reduce mass of existing design, etc.) (Krish, 2011). When leveraging topology optimization, or similar design optimization systems, there is minimal human involvement. The human inputs a design along with associated constraints (e.g. safety factors, etc.) into the system, which automatically evaluates solutions and outputs a single, optimized solution by altering design geometry. Since design optimization minimizes the role of the human, the output is the result of what the selected optimization system believes is the optimal solution. This may not always be the actual optimal solution due to potential challenges in manufacturing complex geometry or usability (e.g. output may not have the human element (comfort, etc.) considered). Furthermore, these systems rarely promote human creativity and as a result design trade-offs may not be considered since a human is best adapted to perform insightful balancing of requirements.

then the generative design output would have been different between participants, thereby presenting other factors that would have altered survey responses. As such, participants were instructed to use a demo file that came pre-installed with Fusion 360. The demo file used was the ‘Explore_Motorcycle Triple Clamp’ file, which contains 53 unique design solutions for a motorcycle triple clamp, see Figure 1 below. Participants were provided a brief scenario on why they were using this file in the study, as well as the function of a motorcycle triple clamp. They were told they were part of a design team that was designing a new motorcycle, and had input several design constraints (e.g. volume, mass, and safety specs) into Fusion 360, which produced the multiple design alternatives found in the study file. They were then told to follow the task instructions to review the design solutions for use in this new motorcycle.

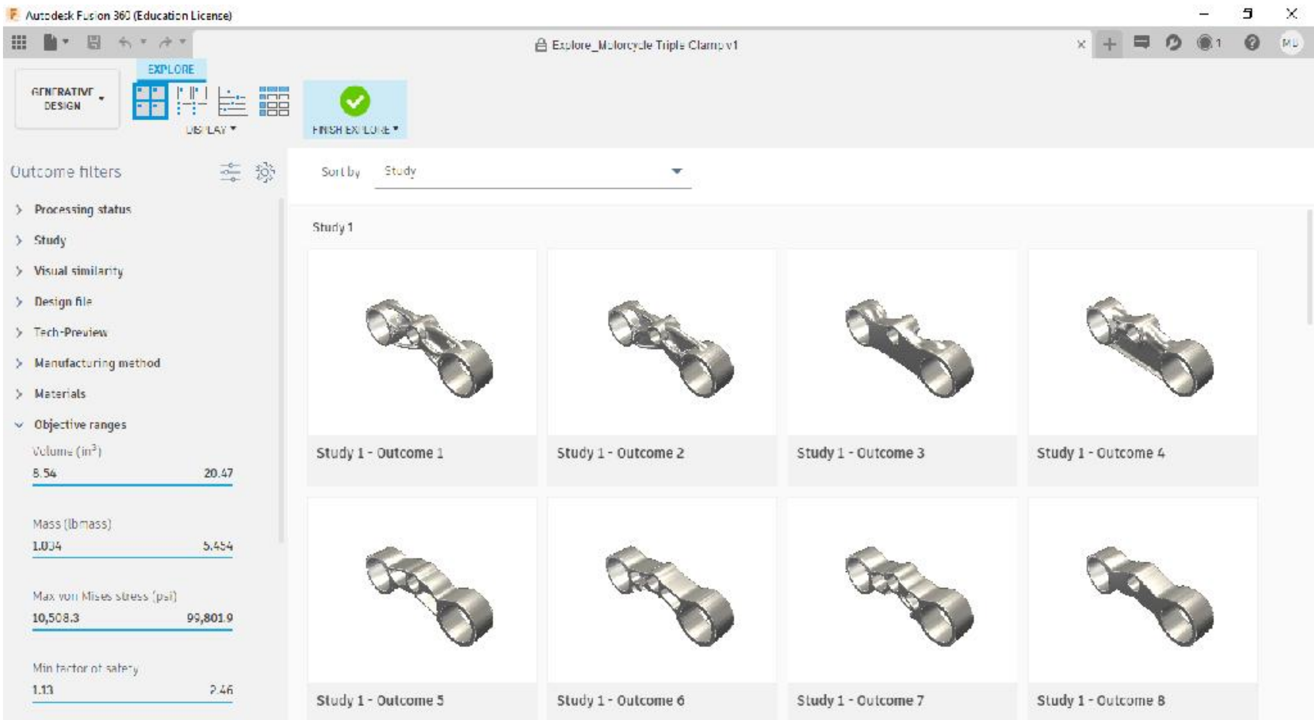

Figure 1. Fusion 360’s Partial Solution Space for a Motorcycle Triple Clamp

MATERIALS & METHODS

A usability study was conducted to evaluate human factors considerations for generative design tool outputs. Participants completed a task using a common software program used in generative design and then answered survey questions regarding their experience. This study had approval from the Colorado State University’s Institutional Review Board (IRB), protocol 20-10385H.

Participants: There were 28 participants that completed this study. All of the participants were graduate students from the Systems Engineering Department at Colorado State University, which is a predominately online graduate program. As such, the majority of the participants were full-time systems engineering industry workers in addition to being graduate students. Graduate students in the department were invited to participate in the study, via email, if they were familiar with the concept of generative design and had some CAD experience.

Software: Autodesk Fusion 360 was used as the generative design tool for this study. Since all of the participants were students, they were able to download the software for free using the educational license.

Generative Design Space Overview: In order to ensure validity of the data, all participants were given the same, pre-generated design file to analyze. If participants created their own solution to the problem,

Task: Participants completed the experiment on their own computer. The entire task took about 30-45 minutes to complete. Each participant was emailed the same set of instructions and a link to the survey. The instructions were divided into four sections, for a total of 13 steps. The first section instructed them on how to download the educational version of Autodesk Fusion 360. The second section directed them to the Fusion 360 demo file named ‘Explore_Motorcycle Triple Clamp.’ The third section provided instruction on comparing the design outputs, by guiding them to look through all the different designs and utilize various filters. Participants were told within each of the steps what survey questions they would be asked related to that step. The final section of the task instructions directed them to the online survey link.

Survey : The survey was developed and administered using Qualtrics Online Survey platform. The survey included 5-point Likert scale questions regarding their satisfaction with the quality and quantity of design solutions, their ability to identify differences in design solutions using various filters, and their opinions on limiting the design solution space. Each Likert scale question also had a text input box, for them to justify their responses. The survey also asked participants about their previous experience with generative design.

RESULTS & DISCUSSION

Experiment results were collected anonymously from participants using Qualtrics Survey Software. Data analysis was conducted in RStudio (version 1.2.5001). The following section presents the results of this experiment and discusses potential impact on generative design output.

Participant Demographics: This experiment was conducted with 28 graduate students studying systems engineering at Colorado State University. Since this experiment pertained to generative design, it was necessary to determine the experience level every participant had with generative design tools and concepts prior to participating in this experiment. Of the 28 students, 26 of them had one year or less of generative design experience; whereas the remainder had between 7 and 12 years of generative design experience. This is an important demographic since those participants with less experience in generative design may not have strong opinions regarding generative design output, however they may have novel ideas based on their unique engineering backgrounds. Likewise, those with significant generative design experience may have strong opinions and be aware of bottlenecks in generative design processes.

Satisfaction of Solutions: Figure 2 below displays data regarding participants' opinions about the quality and quantity of generative design solutions of the Autodesk Fusion 360 generative design tool presented in this experiment. Analysis of the data indicates that the majority of participants were satisfied with the quality and quantity of generative design solutions. Participants stated that the generative design tool provided a novel solution set with design solutions based on multiple criteria that encompassed a broad range of the overall design envelope. Recall that in this instance, the generative design tool presented 53 unique solutions. It is important to note that problems with increased complexity, a broader range of parameters (e.g. material options, etc.), and an iterative design cycle would produce a larger set of design solutions, which could impact the user's perceived levels of satisfaction with the quality and quantity of design solutions.

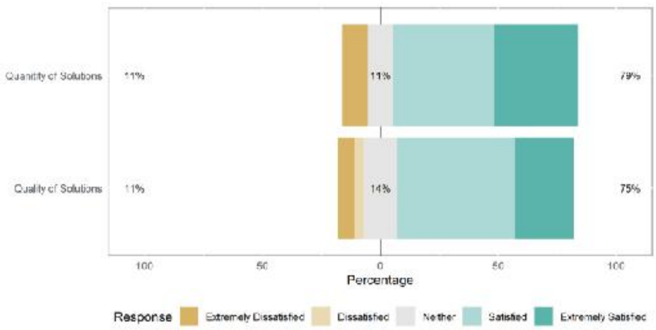

Figure 2. Satisfaction of Solutions

Ability to Identify Differences: Figure 3 below displays data regarding participants' opinions about their ability to differentiate between generative design solutions by using generative design tool filters. When the 'study' filter is applied, the generative design tool simply displays all 53 solutions for the study without any grouping or analysis. Therefore, this could be considered as if no filter were applied. The data indicates that when no filter was applied, participants were nearly split when it came to detecting differences between solutions, meaning nearly half believed it was extremely difficult to detect differences between solutions and the remainder believed it was extremely easy to detect differences between solutions. When applied, the visual similarity filter groups similar solutions (e.g. shape) and created 16 subsets of these similar groups from the entire solution set with each group containing between 2-4 solutions. Along with the groups, the filter identified 13 solutions as unique, meaning they were not assigned to a group. With the visual similarity filter applied, the data indicates that participants were able to improve their ability to detect differences between groups of solutions when compared to their ability to detect differences with no filter applied. With the same filter applied, the participants' ability to detect differences between solutions within the same subset (e.g. group) also increased when compared to detecting differences between subsets and detecting differences with no filter applied. This indicates that filtering a design solution based on visual similarity features of a design, such as shape, increases the ability of users to detect differences between the design.

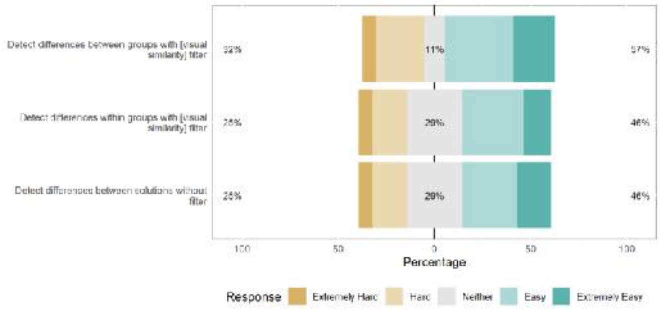

Figure 3. Ability to Identify Differences

Perception of Existing Filters: Figure 4 below displays data regarding participants' opinions about how useful existing filters (e.g. visual similarity, etc.) would be in identifying unique solutions if substantially more generative design options were generated. The majority of participants indicated that leveraging existing filters would be useful in analyzing a scenario with substantially more generative design solutions. This indicates that initial perceptions of a design, such as shape, play a significant factor in a designer's ability to process design alternatives.

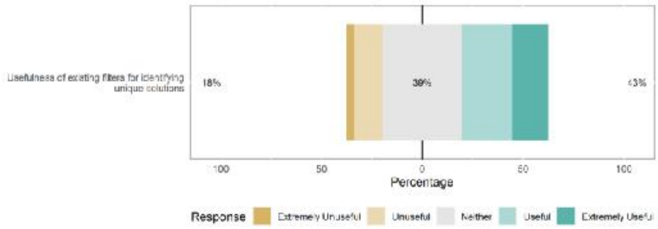

Figure 4. Perception of Existing Filters

Optimal Quantity of Solutions: Figure 5 below displays data regarding participants' opinions about how useful limiting the quantity of solutions generated by a generative design tool would be, provided that novel solutions remain. The data indicates that the vast majority of participants believe that the quantity of generative design solutions a generative design tool provides should be limited. This would enable more efficient systems engineering processes since designers would require less cognitive workload to parse a limited subset of an entire design solution space. Furthermore, reviewing less generative design solutions would correlate to reduced costs, particularly if an algorithm was able to assist with the reduction of available design alternatives.

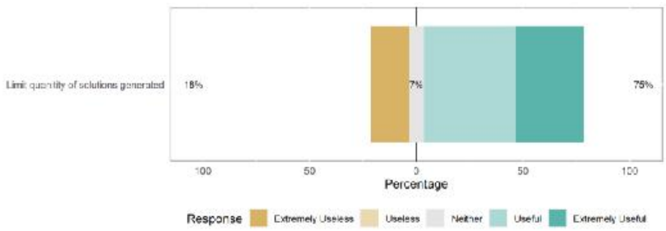

Figure 5. Limiting Quantity of Solutions

Figure 6 below displays data regarding participants' opinions regarding the optimal quantity of generative design solutions for the scenario in the experiment as a percentage of the design solution space provided by the generative design tool. The data indicates no strong preference for the quantity of design solutions for the scenario in the experiment. The ambiguity of this data could be attributed to the level of experience with generative design tools of the participants. Since the majority of participants were students that had little to no previous experience with generative design tools, they likely do not have a strong opinion. Furthermore, this experiment only presented participants with 53 design options, which is not as many as the tool is capable of generating for substantially more complicated applications. Therefore, with an already limited quantity of solutions, there may have been a clear need to further reduce the quantity of the solutions in the experiment.

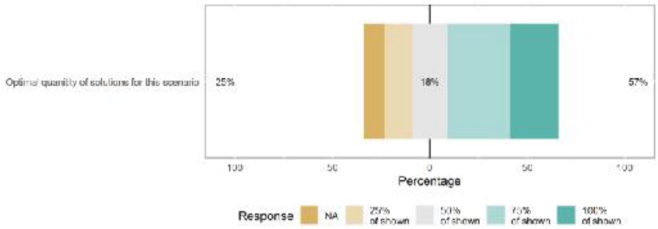

Figure 6. Optimal Quantity of Experiment Generative Design Solutions

Figure 7 below displays data regarding participants' opinions regarding how many generative design solutions a generative design tool should produce in general, particularly when faced with a significantly more complex problem than the one presented in this experiment. The data indicates that the majority of the participants believe 100 or less generative design solutions is the optimal quantity that should be presented to a designer. Indeed, more than 100 solutions will likely place a high cognitive burden on the designer and negatively impact systems engineering processes.

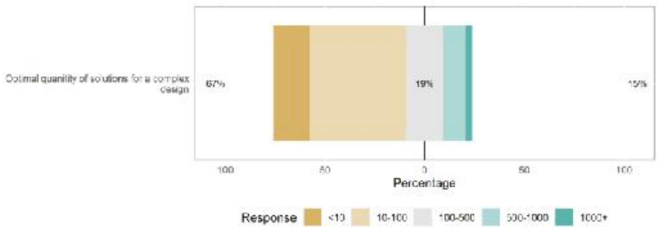

Figure 7. Optimal Quantity of Generative Design Solutions

Conclusion & Future Work: Generative design is a powerful tool that could assist designers with producing novel solutions that address complex problems (2). Although generative design systems have myriad benefits they can provide to modern system engineering processes, the systems must be usable from the human perspective to be leveraged successfully. In order for systems to be usable, through the support of human centered design, a combination of the following elements must be incorporated, including (1) drafting and planning for human-centered design processes, (2) understanding the context of use for the system as a basis for identifying requirements and evaluating the system, (3) understanding and specifying user requirements in a clear manner which can be assessed for achievement, (4) developing a system and user interface based on a flexible and iterative approach, and (5) performing an usability evaluation based on expert and user testing throughout system design (12). Therefore, a successful generative design system would incorporate these elements. This study performed an usability evaluation to obtain feedback regarding the elements of generative design tool output by using Autodesk Fusion 360 and a predefined solution space. Participants that completed the experiment agreed that although generative design is a powerful tool, the main area for improvement is developing tools for effectively parsing generative design solutions. The study indicated that filters, such as visual similarity, are useful in evaluating a generative design solution set. Filters could be used to parse through solutions sets with substantially higher volumes of solution instances. Furthermore, study results indicated that there needs to be a medium to limit the overall quantity of generative design solutions presented to the designer. A solution set with a significant quantity of solutions would likely impair the designer's ability to select an alternative and limit the benefit of the generative design tool. This study presents several areas for future research, including (1) determining how user satisfaction with generative design solution quality and quantity is impacted when more than 50 solutions are generated, (2) determining if generative design filters decrease designer cognitive workload and improve efficiency in systems engineering processes, (3) determining types of filters, aside from visual similarity (e.g. shape), that would be efficiently process a large set of generative design solutions, (4) determining if artificial intelligence (AI) and algorithms can automatically reduce the design space while retaining novel solutions, and (5) determining how human cognitive ability is impacted by various quantity levels of generative design solutions.

Declaration of Competing Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appearedto influence the work reported in this paper.

Acknowledgements: We would like to thank Ingrid Bridge for assisting with soliciting participants for this study. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

REFERENCES

Blanchard B, Fabrycky W. Systems Engineering and Analysis. John Wiley & Sons, Inc. 2004.

Krish S. A practical generative design method. CAD Comput Aided Des 2011;43:88–100. https://doi.org/10.1016/j.cad.2010.09.009.

McKnight M. Generative Design: What it is? How is it being used? Why it's a game changer. KnE Eng 2017;2:176. https://doi.org/10.18502/keg.v2i2.612.

Kazi RH, Grossman T, Cheong H, Hashemi A, Fitzmaurice G. DreamSketch 2017:401–14. https://doi.org/10.1145/3126594.3126662.

Song PP, Qi YM, Cai DC. Research and Application of Autodesk Fusion360 in Industrial Design. IOP Conf Ser Mater Sci Eng 2018;359. https://doi.org/10.1088/1757-899X/359/1/012037.

Bentley PJ, Corne DW. An introduction to Creative Evolutionary Systems. Creat Evol Syst 2002:1–75. https://doi.org/10.1016/b978-155860673-9/50035-5.

Fischer T, Herr C. Teaching generative design. … 4th Conf Gener Art 2001:1–14.

Helander MG, Tham MP. Hedonomics - Affective human factors design. Ergonomics 2003;46:1269–72. https://doi.org/10.1080/00140130310001610810.

Garneau CJ, Parkinson MB. Considering just noticeable difference in assessments of physical accommodation for product design. Ergonomics 2013;56:1777–88. https://doi.org/10.1080/00140139.2013.838308.

Piasecki M, Hanna S. A redefinition of the paradox of choice. Des Comput Cogn '10 2011:347–66. https://doi.org/10.1007/978-94-007-0510-4_19.

Kida T, Moreno KK, Smith JF. Investment Decision Making: Do Experienced Decision Makers Fall Prey to the Paradox of Choice? J Behav Financ 2010;11:21–30. https://doi.org/10.1080/15427561003590001.

Maguire M. Methods to support human-centred design. Int J Hum Comput Stud 2001;55:587–634. https://doi.org/10.1006/ijhc.2001.0503.

****