The Pennsylvania State University
The Graduate School

DESIGN FOR INSPECTABILITY: INVESTIGATING THE EFFECT OF INSPECTABILITY CONSTRAINTS ON DESIGNS AND DESIGN STRATEGIES

A Dissertation in
Mechanical Engineering

by
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Submitted in Partial Fulfillment
of the Requirements
for the Degree of

Doctor of Philosophy

August 2021

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ABSTRACT

Components manufactured with Additive Manufacturing (AM) can feature high levels of geometric, material, and functional complexity. Designers can use AM technologies to create components with more complexity than was possible with traditional manufacturing methods. However, highly complex components can be difficult to inspect using existing Non-Destructive Evaluation (NDE) methods. Professional organizations like the Additive Manufacturing Standardization Collaboration (AMSC) have suggested that designers should keep quality in mind during the early stages of design. The Design for Inspectability (DFI) Framework is proposed in this work to help designers consider quality early in design. Based on recommendations from AMSC, ultrasonic testing was selected as the first modality of NDE for which DfI considerations were developed. Through open and axial coding of literature, a set of DfI heuristics was developed for ultrasonic testing. These heuristics were organized into a design tool, the DfI worksheet, to facilitate design studies. First a controlled study with 12 designers from The Pennsylvania State University suggested that introducing DfI considerations may indeed help designers to increase the inspectability of designs. A second study with 20 designers was performed to determine what effect DfI considerations have on design outcomes. Quantitative methods, including static structural analysis of generated designs and simulation of ultrasonic wave propagation, were used to compare the design outcomes of designers introduced to DfI considerations to those in the control group. Results of this test suggest that design outcomes, including inspectability, may not be significantly impacted. Tools including the NASA Task Load Index (NASA-TLX), Linguistic Inquiry and Word Count (LIWC), and Hidden Markov Modelling were used to determine what effect introduction of DfI considerations would have on designers and the design process. Cognitive and design processes are impacted by the introduction of DfI considerations, with a decrease in cognitive processes likely contributing to changes in designer strategies. Continued development of the DfI framework is recommended to ensure designers can create components inspectable using existing NDE technologies.

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ACKNOWLEDGEMENTS

I would like to thank my wife, Melissa, without her I would not been able to make it through grad school.

A special thanks to my parents, who have always encouraged me to continue my education. Yes, I will finally go out and get a job.

Thanks very much to my advisor, Dr. Jessica Menold. There were many times I nearly quit, but your encouragement always brought me back.

Thank you to all those who offered advising and advice, it truly takes a village to complete a dissertation.

Thank you to all those who helped me process data, including Micaela Stover, Lauren Katch, Pratima Saravanan, and Hannah Nolte. Without you, this dissertation would've been delayed until at least Fall semester.

A special shout-out to Good Day Café, where I wrote at least half of this dissertation. Thank you so much for my daily large Chai Latte, hot, with almond milk, and a blueberry scone.

To all those that I could not mention by name, thank you for the part you played in getting me to where I am today. I wish I could thank each and every one of you individually, but I only have one page for acknowledgements, and this draft has to go out by 5.

Chapter 1

Introduction and Motivation

Additive manufacturing (AM), sometimes referred to as 3D printing, is growing rapidly, with a compound annual growth rate of 14.4 percent in 2018 [1]. Originating in the early 1980s with Stereolithography (SLA), 3D printing was originally used for visualizing 3D models [2]. This technology has expanded to include seven types of 3D printing: SLA, Material Extrusion (ME), Powder Bed Fusion (PBF), Material Jetting (MJ), Binder Jetting (BJ), Directed Energy Deposition (DED), and Sheet Lamination (SL) [3]. Many of these methods are now being used in the production of end-use products [4]. The aerospace, automotive, and medical industries, in particular, have seen early adoption and a high growth rate of AM in end-use product production [1]. Many of these end-use products are safety-critical components, such as load-bearing components and fuel injectors in the aerospace industry [5–7], brake assemblies in the automotive industry [8,9], and implantable medical devices in the medical industry [10,11]. For such components, it is important they function correctly and reliably, as a single failure could pose a serious risk to human life.

The American Society of Mechanical Engineers [12], the American National Standards Institute (ANSI), and America Makes [13], all cite a lack of standards regarding quality control or certification of AM parts as a significant barrier to continued industry adoption of AM. To help fill the need for adequate standards, a collaboration between ANSI and America Makes known as the Additive Manufacturing

Standardization Collaboration (AMSC) identified 95 gaps in current practice that required one or more standards to improve quality control [13]. These gaps fall into eight categories, including design, precursor materials, process control, post-processing, finished material properties, qualification and certification, non-destructive evaluation, and maintenance and repair [13]. One of the listed gaps, gap D26: Design for Measurement of AM Features, suggests that designers must consider available methods of testing and determine if appropriate methods of QA/QC are available.

The unique capabilities of AM pose new challenges for ensuring quality using existing technology and techniques [14]. The qualification and certification of AM parts is critical to ensure the safety of users, but quality assurance methods and certification techniques have not kept pace with the rapid advances of AM technology [15–17]. The complex geometry seen in many AM designs limits access of measurement tools such as micrometers, touch probes, and laser scanning systems [18], and features such as microstructure or internal geometry requires specialized equipment for accurate characterization [19–21]. As AM continues to influence the field of design, it is imperative that designers consider the true cost of complexity afforded by AM technologies, specifically with regards to final part inspection and qualification.

If appropriate technology is unavailable to inspect a complex component, the part must either be re-designed or new methods of inspection must be developed, either of which can greatly increase development costs and time-to-market of AM components. It is unreasonable to expect designers to be familiar or knowledgeable of the numerous NDT technologies available and the corresponding design constraints of each. If provided with a tool that complimented design knowledge with NDT knowledge, designers could make early design choices that help ensure components can be efficiently and effectively inspected, such that all defects can be identified and characterized.

Purpose of the Study

Additive Manufacturing sits at the crux of a paradigm shift, and designers need a novel framework to help them navigate emergent constraints. Thus, this work proposes a novel Design for X (DfX) framework to help designers consider inspectability constraints during early-stage design processes. For such a framework to be useful, it must be usable by designers and must include simple and actionable heuristics. It is important to understand how such a design framework will affect the design process, including the impact on design outcomes and the impact on designers themselves. Thus, the Research Questions are:

1) *What effects do Design for Inspectability considerations have on design outcomes, including inspectability*?
2) *What effects do Design for Inspectability considerations have on designers and the design process?*

If inspectability constraints fail to help designers increase the inspectability, then it will not provide benefit to designers, and will require further development before being used in industry. If inspectability constraints do help designers make designs which are more easily inspected, but significantly worsens design outcomes or makes it difficult for designers to meet other design objectives, then further study will be required to determine if and how inspectability constraints will be applied during the design process. Finally, if introducing inspectability constraints does significantly alter designer strategies and decision making, careful consideration of how such constraints are applied is required, so they do not prevent designers from effectively utilizing other design practices used in industry.

The heuristics and tools proposed in this work represent the first fundamental step in addressing the need for designers to consider inspectability. By studying the use of these tools in controlled studies with real designers, metrics are recommended with which future design for inspectability tools can be measured. Looking at the outcomes of these controlled studies, next steps are identified in developing tools, practices, and standards for inspectability. Continuing research and fostering collaboration to complete these next steps, the Design for Inspectability framework will evolve alongside continued development of AM and NDT technologies.

Outline of Dissertation

This dissertation is organized into seven chapters that describe the creation and evaluation of a DfI framework. In the second chapter, literature is reviewed about current non-destructive testing (NDT) methods and current Design for X (DfX) frameworks. Next, a preliminary study is discussed in which design heuristics and a DfI worksheet were developed, as well as the results of an initial in-depth design study by a group of 12 designers. Following this, in chapter 4, the effect of DfI on design outcomes are reviewed, leveraging data from a controlled virtual study. In chapter 5, the impact of DfI on designers' strategies and decision making is evaluated using qualitative and quantitative methods. The implications of results for the field and industry more broadly are discussed in chapter 6, with attention to current and future research endeavors.

Chapter 2

Theoretical Linkages and Basis for DfI Framework

2.1 Quality Assurance and Quality Control of AM Components

QA/QC can add significant cost to component manufacturing [22,23]. The cost required to inspect products can be considerable, and has been studied by researchers interested in understanding the cost of quality [22,24–26]. This cost can include any expenses associated with ensuring good quality, as well as any losses that occur due to poor quality [24,25]. Currently, companies try to increase efficiency by minimizing Type I errors, categorizing in-tolerance parts as non-conforming by mistake, and Type II errors, categorizing out-of-tolerance or defect parts as fit for consumer use [27]. Prior work has demonstrated that when designers consider the inspection of parts early in the design process, they can reduce cost of quality by preventing redesign, relaxing tolerances on non-critical features, and avoiding the need for custom fixturing required for accurate metrology [28,29]. Through implementation of frameworks such as Quality by Design, designers can help reduce costs associated with ensuring quality [30].

AM methods pose unique challenges in terms of QA/QC. The Air Force Research Laboratory (AFRL) created a system for rating parts based on their complexity [31]. Parts could be categorized as simple tools and components, optimized standard parts, embedded features, designed for AM, and lattice structures. According to the AFRL, parts with embedded features have no clear line of sight; this added complexity reduces the number of applicable NDE technologies. Additionally, parts designed for AM "have greatly reduced inspectability because surface areas have increased and the vast majority of the structure is very detailed and embedded." Finally, of lattice structures, the AFRL document postulates that "new or creative application of existing NDE technologies would be required for inspection" [31].

Most current research in QA/QC for AM components focuses on in-situ monitoring [32–35] and Computed Tomography (CT) [21,36,37]. In-situ monitoring involves the capture of machine parameters and part conditions throughout a print using methods such as thermography [38,39], ultrasonic testing [40], and acoustic emission [14], among others. By capturing data regarding thermal history or material deposition rate, it may be possible to predict quality metrics such as porosity or thermal stress build-up [32–34,41]. These methods, while important in providing feedback control to improve part quality, may not accurately predict all properties of a final printed component due to high levels of uncertainty [42]. Using process parameters to predict structure, properties and performance of AM components is a complex problem that involves many confounding factors [43]. The Additive Manufacturing Center of Excellence(AMCoE) has called for standards of in-situ monitoring [44], acknowledging there is no well-established process to extract information from in-situ monitoring techniques for quality evaluation. In-situ monitoring is also not an appropriate inspection technique for processes with significant post-print processing, such as Binder Jet technologies, where post-print sintering can result in significant geometric changes [45]. Finally, much of the in-situ methods currently being investigated are incredibly nascent, and further testing is needed before they can be widely implemented in industry [32,34,46,47].

Statistical methods such as acceptance sampling have traditionally been used to create inspection plans, and can play a significant role in the cost of quality [23,26,27]. However, such methods may not be appropriate for AM. When using AM to produce parts in large batch sizes, rare defects can arise that greatly diminish mechanical properties such as strength and ductility [48]. In such cases, sampling techniques may be inadequate, failing to detect defective parts, putting end users at risk. For this reason, safety-critical components produced with AM may need to be inspected with non-destructive testing to ensure all components meet performance standards and requirements.

There are thirteen methods of non-destructive testing (NDT) recognized by the American Society of Non-Destructive Testing (ASNT) [49]. Among these methods, six are listed as the most commonly used: Magnetic Testing (MT), Liquid Penetrant Testing (PT), Radiographic Testing (RT), Ultrasonic Testing (UT), Electromagnetic Testing (ET), and Visual Testing (VT). Among these methods, MT, PT, and VT are listed as methods for characterizing features along the surface of a part, and ET is used for the testing of tubular and bar like products [49]. This means that RT and UT are most apt for inspecting complex AM components particularly for internal flaws or defects.

Methods included in RT, such as Computed Tomography (CT), make use of ionizing radiation for measuring internal and external parts of a component [50]. Since ionizing radiation experiences low levels of attenuation as it passes through physical material, it can be used to measure the interior portion of components within a range of thicknesses [19,47]. However, considerable infrastructure is required to prevent exposure of personnel to radiation. This raises the bar for entry beyond what most small to medium enterprises (SME) can attain [20]. In addition, the time and expense associated with image reconstruction [20,51] means CT may not be an appropriate solution for all components, particularly those produced in large batch sizes.

Methods included in UT make use of ultrasonic waves that propagate through material and can reflect or refract off of material interfaces [52]. Numerous UT methods exist, including Pulse-Echo Ultrasonic Testing (PEU), Through Transmission, Immersion Testing, and Laser Ultrasonic testing [40,53]. All ultrasonic testing methods share some basic principles which enable the characterization of surface, near-surface, or deep features. Ultrasonic waves are categorized by their motion, with longitudinal waves (P-waves) oscillating parallel to the direction of wave propagation, transverse waves (S-waves) oscillating perpendicular to the direction of wave propagation, and surface waves oscillating at or near the part surface. Ultrasonic waves are created when electrical energy is converted to mechanical energy through a device known as a transducer. Ultrasonic waves radiate out from where they were created. The strength of the wave is greatest along a line perpendicular to the direction the wave is propagating, known as the acoustic axis. Ultrasonic waves experience a level of resistance to propagation through any given medium. This level of resistance, known as ultrasonic impedance value, is unique to each medium determined by the mechanical properties of that material. Whenever an ultrasonic wave encounters a location of two materials with different ultrasonic impedance values, a location also known as a material interface, there is a chance that a wave will reflect or refract. The level to which the wave reflects or refracts is determined by the angle at which the wave meets the material interface, also known as the angle of incidence, and the difference in impedance value of the two materials at the interface. By measuring the ultrasonic waves at points along the surface of a part with one or more transducers, it is possible to construct an image of sites where reflection and refraction occur. With enough data, it is possible to accurately characterize features at the surface, near the surface, or deep inside a part.

While each method varies in how ultrasonic waves are induced or measured in a part, they share many of the same advantages and limitations. Methods in UT can be used to detect flaws deep inside a part. They can be used to determine the size, shape, and location of features inside the volume of a part, and can provide results almost instantaneously [52–54]. Ultrasonic waves produce no ionizing radiation, reducing risk to operators as compared to RT. However, components that have a rough texture, an irregular surface, or are made of multiple materials may be difficult to inspect using UT [52].

Researchers within post-processing inspection are actively seeking improved inspection methodologies developed specifically for AM [55–57], which will facilitate quality assurance of end use components with intricate geometries and features. However, these techniques are far from suitable maturity and robustness and have high costs associated with implementation in production lines. Therefore, there is still a latent need for part qualification using conventional NDT methods. Incorporating NDT considerations early into the design process could increase the likelihood that final parts are *inspectable*, reducing the cost of QA/QC and post processing.

2.2 Design for X Frameworks

A Design for X (DfX) framework is an established set of tools and knowledge that allows designers to improve a design along a set of chosen metrics [58]. Many DfX frameworks exist, including Design for Manufacturing and Assembly (DfMA), Design for Quality (DfQ), Design for Reliability (DfR), and Design for Additive Manufacturing (DfAM) [58]. In each of these frameworks, suggestions made early in the design process are used to affect many downstream design outcomes, helping improve design outcomes with respect to a stated objective (i.e. reduction of manufacturing time, cost, or resource use).

The earliest example of a DfX framework was the Design for Assembly (DfA) introduced by Boothroyd and Dewhurst [59]. The crux of DfA is the proposition that designers can help companies reduce time-to-market and make production more efficient by focusing on ease of manufacturing and efficiency of assembly earlier in the design process. Based on tacit knowledge gained through years of experience in product design and manufacturing and evidence-based literature, the DfA framework provides simple, specific, actionable information for designers who may be inexperienced with traditional manufacturing approaches [60]. Boothroyd and Dewhurst provide numerous examples of designs which function as needed by users but that are difficult for workers to handle and assemble [60]. Rules like "Design parts to be self-aligning and self-locating" and "Ensure adequate access and unrestricted vision", when applied early in the process can vastly improve the efficiency of manufacturing and assembly [60]. These simple rules are examples of design heuristics [61], mental shortcuts that enable experts to make rapid decisions that lead to acceptable design solutions. Unlike optimization processes, using heuristics is not meant to help a designer reach a perfect or optimal solution, instead to reach a sufficient or workable solution quickly. Heuristics are typically derived from expert knowledge and can be applied early in the design process [62]. In addition to explicitly stated heuristics, a number of tools were presented in Product Design for

Assembly [60] to aid designers, including a manual handling chart, manual insertion chart, and a design for manual assembly worksheet. These tools decrease time to market, as designers can apply necessary changes to their design before sending it “over the wall” to the manufacturing team, reducing the number of times designs must change hands [63]. Since adoption of DfA and DfM, countless areas have emerged, including Design for Lifecycle [64] or Design for Reliability [65], each sitting under the umbrella of Design for X. Often new areas or “Xs” emerge as novel technologies fundamentally shift or change the product development process, requiring designers and companies to adapt in order to remain competitive in a global market.

With the rise in popularity of AM, research has focused on the development of DfAM. Frameworks, tools, and methods in DfAM may be classified as restrictive or opportunistic. For designers unfamiliar with the advantages over traditional manufacturing approaches, opportunistic DfAM shows the opportunities for “free” and “unlimited” complexity, increases design freedom, and encourages creativity [66,67]. For designers unfamiliar with the limitations of AM machines and materials, restrictive DfAM presents designers with rules of best practice to create design that can be printed consistently and without error [68,69]. Restrictive DfAM has been proven to decrease the rate of print failure [70] and the amount of waste produced via failed prints [71]. Opportunistic DfAM encourages designers to utilize the unique strengths of AM that were not possible via traditional manufacturing methods [72]. Opportunistic heuristics have been shown to increase the number of unique or novel ideas produced during ideation [73]. Studies suggest that novice designers need to be exposed to both opportunistic and restrictive DfAM to create designs that are both novel and feasible [74]

Design for Inspectability is not an entirely new concept. Reviewing prior work, we see the concept of inspectability emerge within aerospace engineering as early as the 1960s. Wannlund [75] developed recommendations for part geometry to reduce the need for x-ray inspection of welds for space shuttle components. At the time, uncertainty in the interpretation of x-ray images was great enough that experts were unable to tell if welds would fail during shuttle launch. Parts were redesigned to minimize this risk by reducing the effort required to effectively inspect components using visual inspection techniques. More recently, Stolt et al. [76] developed an inspectability index to describe how inspectable aerospace parts were, in the context of Fluorescent Penetrant Inspection (FPI) techniques, the most sensitive method for detecting cracks in the surface of welds [77]. Stolt et al. created an automated tool which assigns an inspectability index score to a component based on the geometry of the part and the proposed manufacturing technique. This inspectability index allowed engineers to directly compare designs based on the ease of inspection using FPI. Much of this prior work, however, has investigated the inspectability of components within a subtractive or traditional manufacturing paradigm [76], and we argue that a novel Design for Inspectability (DfI) framework is necessary to meet the needs of rapidly evolving AM technologies.

2.3 Synthesis of Literature and Scope of Dissertation Work

The complexity of components that can be produced with AM poses unique challenges for QA/QC. Based on the level of complexity, some NDE methods may be difficult or prohibitively expensive. For complex AM components with internal features, the most apt forms of NDE include RT and UT. Considering the risks, costs, and time required for image reconstruction, inspectability criteria made for UT are most likely to be widely applicable in industry.

Applying criteria early in a design process to affect late-stage design outcomes is a practice found commonly in DfX frameworks. Frameworks like DfA have been shown to reduce cost and time to manufacture. If designers are exposed to inspectability considerations early in the design process, they may produce designs which are more easily inspected using mature NDE like UT. However, to be confident in recommending the use of DfI considerations in industry, those considerations need to be shown to be effective.

Synthesizing the concomitant literature, we highlight the opportunity for a novel DfX framework to increase inspectability of AM components, reducing the cost of redesign and quality assurance. Thus, the aim of the current work is to derive a DfI tool, evaluate its efficacy via controlled studies with designers, and explore the effect DfI considerations may have on designs and designers.

Chapter 3

Creation of DfI Framework

In line with prior DfX frameworks, information in a DfI framework should be simple, specific actionable, and must reliably improve related design outcomes. Measurable design outcomes are thus necessary to assess the effectiveness of a DfX framework. In Design for Assembly (DfA), design outcomes include total handling time and total operating cost [60]. In Design for Additive Manufacturing (DfAM), design outcomes include percentage of failed prints and total mass of waste produced [62,70]. For DfI, the standard by which efficacy of NDT is measured is called the Probability of Detection (PoD) [78]. Experts and researchers use PoD to describe how likely it is to find a defect given a certain NDT method [79]. The most commonly held threshold for PoD is the $a_{90/95}$, a measure of the smallest defect size which can be detected in ninety percent of searches with a ninety-five percent confidence interval. The size of the $a_{90/95}$ is dependent on a number of different factors dictated by the design of a component, including material and geometry [78]. The $a_{90/95}$ serves as a useful metric to evaluate the effectiveness of a DfI framework; theoretically, the smaller the $a_{90/95}$ value the more "inspectable" the component [79].

3.1 DfI Tool Development

Determination of $a_{90/95}$ is highly dependent on the type of NDT being used. To narrow the scope of work, based on Gap D26 in the AMSC standardization Roadmap, ultrasonic testing (UT) was selected [13]. DfI heuristics were developed based on literature discussing the basic operating principles, limitations, and current research in ultrasonic testing. A total of 84 pieces of literature were collected through internet and library searches using the key words “ultrasound probability of detection”, “ultrasound defect detection”, “ultrasound non-destructive testing”, “ultrasonic wave propagation”, and “ultrasound additive manufacturing”. Literature from the years 1980-2021 was included in the search. The literature consisted of three reference texts and eighty-one articles. Eight articles were found specifically describing ultrasonic testing of AM components. The remaining literature described ultra-sonic testing in metallic components, composite materials, and thin-plate structures. The literature was coded using an open and axial coding approach [80]. Open Coding began with immersion in literature. Identification of emergent themes occurred iteratively with a constant comparative approach [81]. Factors affecting wave propagation, signal, strength, reflection, refraction, and Probability of Detection were recorded. Once all literature had been considered in open coding, axial coding was used to eliminate redundant factors and organize factors into groups [81]. Factors which dealt with the same phenomenon of ultrasonic wave induction, propagation, reflection, refraction, or measurement were combined. Combination stopped when all factors were independent, such that changing one factor could change the Probability of Detection without changing any of the other factors. After this, factors were separated into thematic groups. The first theme, machine, are factors that are set in place when the UT equipment is manufactured. The second theme, environment, includes factors determined during equipment installation and maintenance. The third theme, material, includes factors determined when designers or engineers decide out of which material or materials a component will be made but affected by manufacturing process parameters. The fourth theme, geometry, includes factors set when designers create a detail design. The fifth theme, operator, includes any factors that can be changed by a UT technician during inspection using UT.

A modified Ishikawa Diagram shown in Figure 3-1 shows these factors categorized in terms of material, geometry, measurement, machine, and environment. An Ishikawa diagram is useful in root cause analysis for problems with multiple causes [82]. With the five major factors (branches) assigned as 1) material, 2) geometry, 3) measurement, 4) machine, and 5) environment, the Ishikawa diagram features eighteen minor factors (twigs) such as acoustic impedance, surface geometry, and decision threshold.

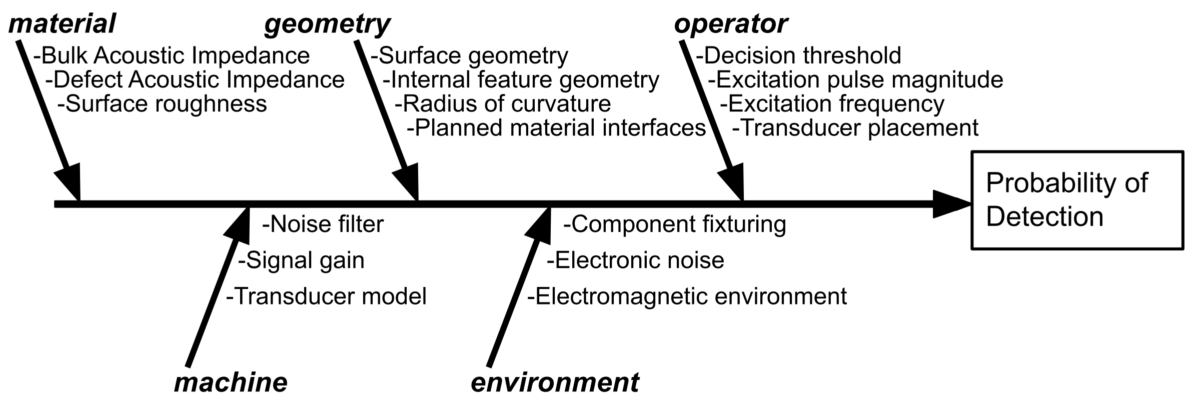


Figure 3-1. Ishikawa diagram with major and minor factors of Probability of Detection

Looking at the Ishikawa diagram, factors like measurement, machine, and environment are likely to be controlled by QA/QC professionals, while factors in the material and geometry categories are more likely to be impacted by early design choices. Based on the minor factors included under material and geometry, a list of simple rules was created to increase the probability of detecting an internal defect in a component or print-in-place assembly, as shown in Table 3-1.

Table 3-1: Evidence-Based Design Heuristics for DfI for Ultrasonic Testing

Heuristic	Reasoning	References
Increase the radius of curvature for a rounded or sharp surface surrounding an important feature	Maximizing the contact area between the transducer and the part ensures maximum energy transmission into the part for inspection.	[40,52,83–85]
Reduce the number of thin, plate-like features	At least one point of transduction is required on each plate-like feature. Large numbers of plate-like features may be difficult or inefficient to characterize.	[52,86–88]
Important features should be placed near the part surface or at a point in line with the transducer	Surface waves can be used to detect features at or near the part surface. P or S waves can be used to detect features deep to the surface if in line with the transducer.	[52,54,84,85,89–94]
Remove a material interface that is between the part surface and an important feature	Reflection and refraction occur at all material interfaces reducing the transmitted energy used for defect detection and localization.	[52,53,85,89,93,95]
Remove a mechanical (mating) interface	Reflection and refraction decrease the power of a signal and can prevent detection of deeper features. Reflection and refraction occur at all material interfaces, including mechanical interfaces.	[52,53,85,93,95]
Add a port to an internal cavity through which liquid can be introduced	Air-solid interfaces inhibit the propagation of ultrasonic waves due to high impedance mismatches. Adding a liquid couplant decreases the impedance difference and facilitates ultrasonic wave propagation.	[52,54,96]

3.2 Development of the Design for Inspectability Worksheet

A worksheet was developed to incorporate these heuristics, as seen in Figure 2. The worksheet was developed as a tool for understanding the impact of Design for Inspectability on designers and design outcomes, while adding minimal additional burden to designers during front end design processes. The first version of the worksheet (Figure 3-2) consisted of seven separate criteria, describing surface geometries, internal geometries, material interfaces, and functional joints.

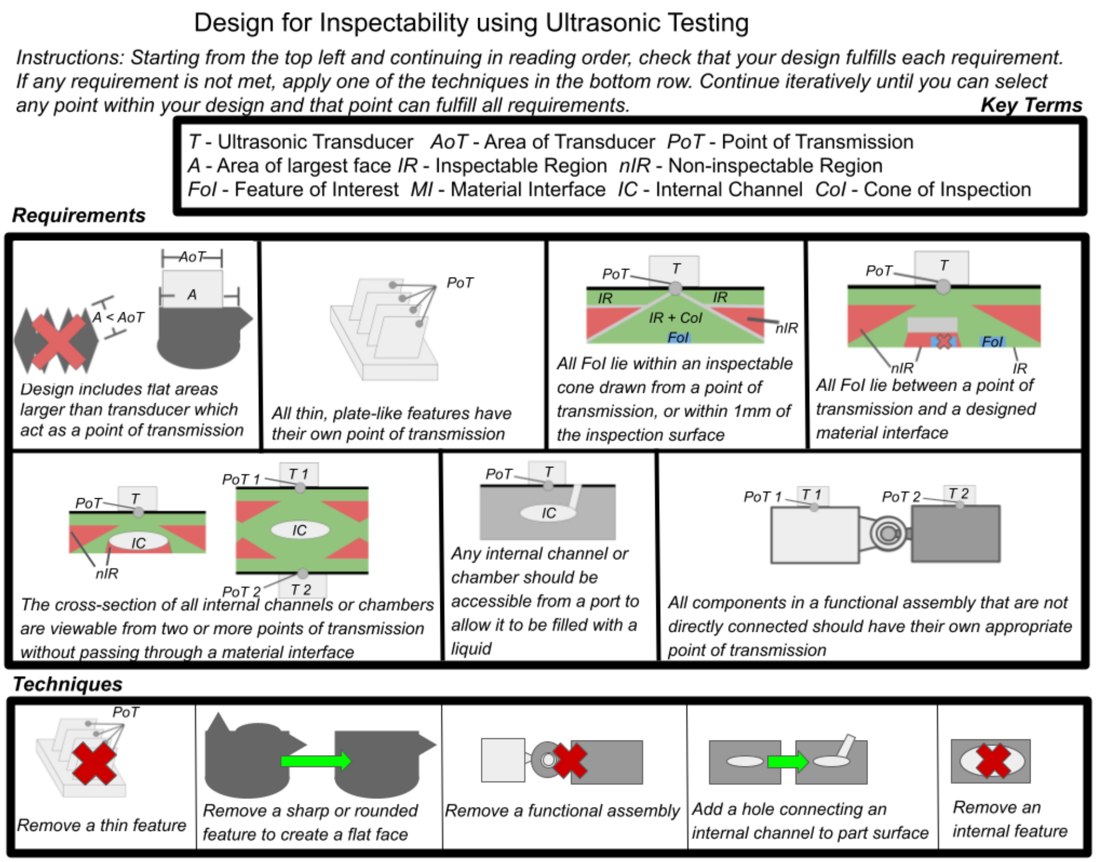


Figure 3-2. Design for Inspectability Worksheet V1

Before the worksheet could be used in a controlled study, it was important to ensure all elements of the worksheet were easy to understand and use by designers. Pilot studies were conducted with five designers to evaluate the usability of the worksheet. Participants were instructed to think-aloud as they assessed the inspectability of parts, including the turbine blade shown in Figure 5A, the bracket shown in Figure 5B, and the GE Engine Bracket shown in Figure 6. Participants were then asked a series of open-ended questions via semi-structured interviews regarding the usability of the worksheet. Questions such as "what is the first thing you do when using the sheet " and "what does this picture tell you" Helped the researcher identify usability issues and improve the worksheet in future iterations.

Based on participant feedback, it was determined that the worksheet needed to be simplified to increase usability. The scope of the worksheet was narrowed to Pulse-Echo Ultrasonic (PEU) testing, a method where the same transducer is used to initiate and measure the ultrasonic waves. Since only one transducer is used for transmitting and receiving signals, designers do not need to consider placement of multiple transducers.

After the scope was narrowed, the worksheet underwent three major revisions, where (1) the seven criteria were condensed into three larger categories, (2) the redesign instructions were replaced with a scoring system, similar to the one used in the DfAM Worksheet [62], and (3) images were revised for simplicity and for clarity. As part of the third revision, key terms on the worksheet were paired with geometric features, and graphics were edited for consistency. For example, the same blue rectangle was used in every image to represent a feature of interest, the same grey rectangle for every transducer, and the same grey circle was used to represent the point where ultrasonic waves are transmitted into the part. The term feature of interest (FoI) refers to flaws, defects, internal geometries, or non-visible faces that may be of importance.

Once updates were made to the worksheet a second pilot study was conducted. First, participants were asked to score parts using the DfI worksheet in Figure 3-3. Participants then sorted example parts into four categories: 1) Accurate inspection possible with PEU, 2) Inspection with PEU may be inaccurate for some Feature of

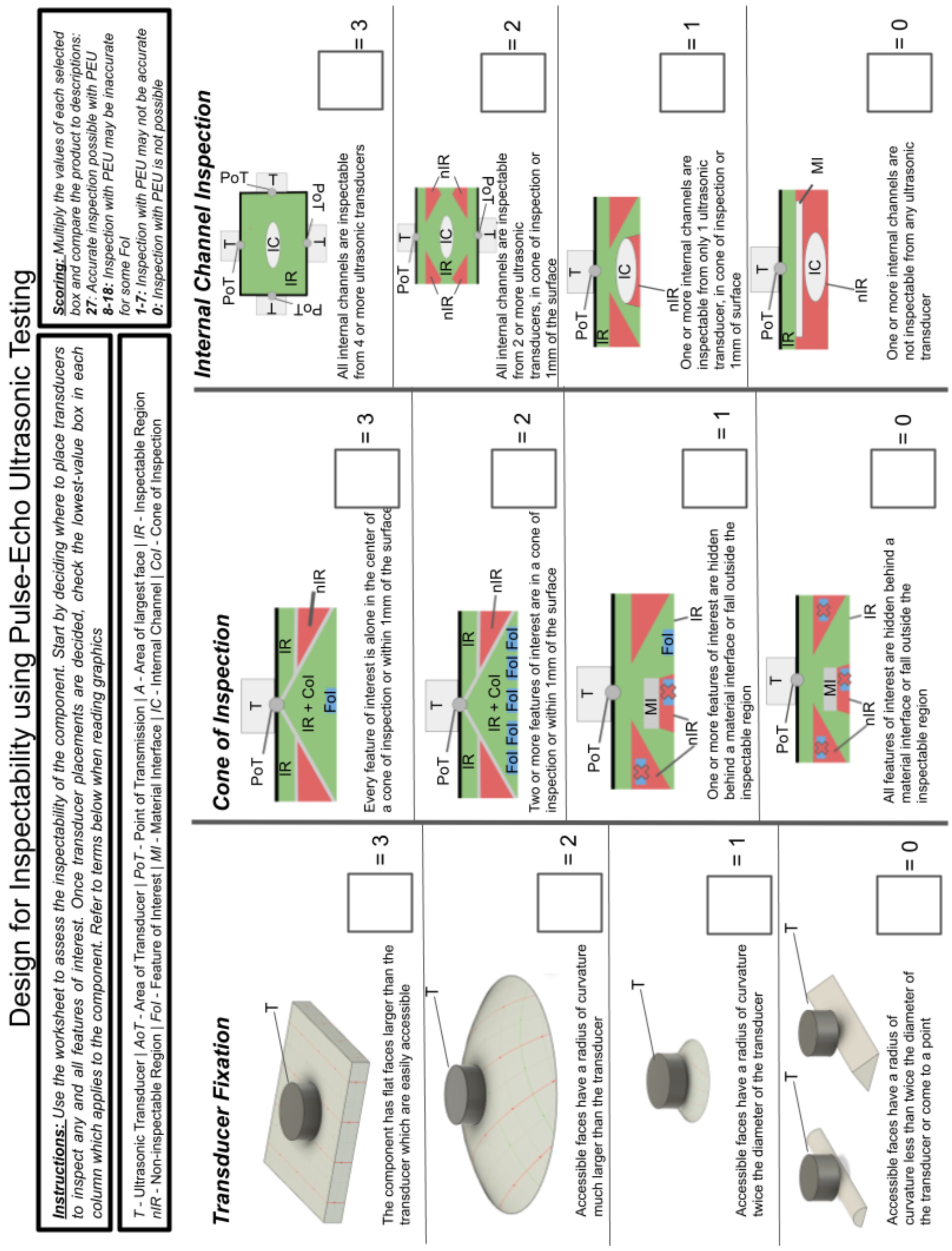


Figure 3-3. Final version of the Design for Inspectability Worksheet

Interest, 3) Inspection with PEU may not be accurate, 4) Inspection with PEU is not possible. Participants' ability to correctly sort CAD models provided a quantitative indicator of the usability of the worksheet. Once participants in the pilot study consistently rated the parts the same as members in the research team (interrater reliability > .75), the DfI worksheet moved on to more formal testing to understand the effects of DfI on downstream design outcomes. The creation of this worksheet is in line with past work and procedures to create similar design tools [62,97], and a more detailed review of the process is outlined in [98].

The flow of the final version of the worksheet is shown in Figure 3-4. Starting in the top-left corner and continuing clockwise, the sheet includes instructions for use, a scoring guide, 3 columns of criteria based on limitations of PEU, and a list of terms to properly read the worksheet. The instructions start with transducer (T) placement; designers decide whether they can place transducers on the surface of the part to measure every feature of interest. Two terms important for using the worksheet –Inspectable Region (IR) and non-inspectable region (nIR) – were created to signify where the feature of interest can be in relation to transducers. Through the pilot study, it was found that these terms were intuitive and readily understood.

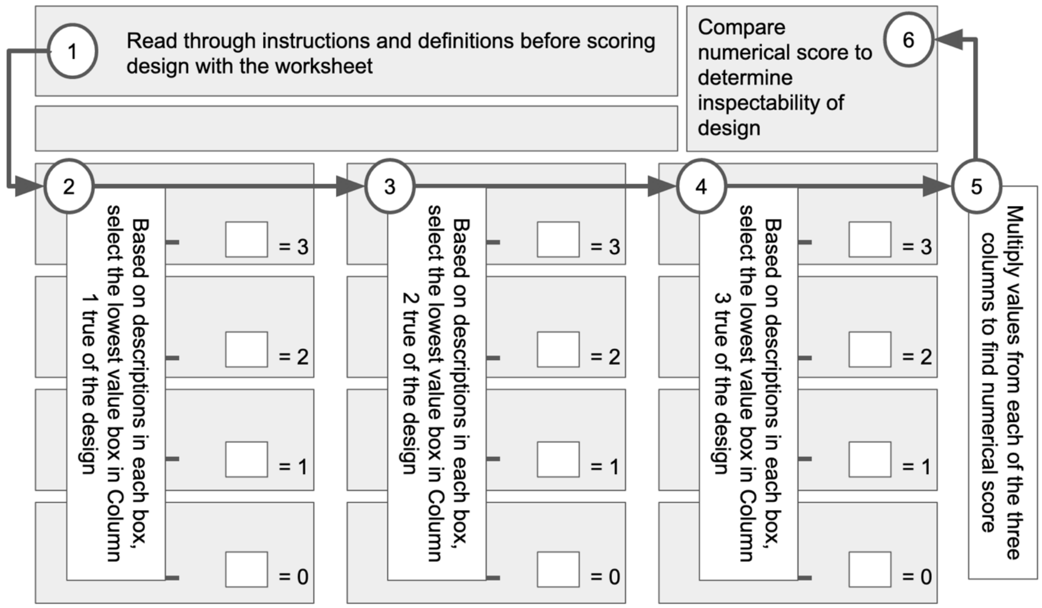


Figure 3-4. Flow of the Final version of the Design for Inspectability Worksheet

After deciding where transducers can be placed, designers evaluate their designs based on three categories: Transducer Fixation (TF), Cone of Inspection (CoI), and Internal Channel Inspection (ICI). Each of these categories is represented by their own column. At the top of each column is an optimal or best-case scenario, an example geometry that would be highly inspectable. At the bottom of each column is a worst-case scenario, an example geometry that would be challenging (or impossible) to inspect. Designers are instructed to consider all features in their design. Starting with the left-hand column, designers mark the lowest box for which they can identify one or more features in their design. After marking a box in each of the three columns, designers can use the numerical value associated with those boxes to calculate their design scores.

In order to calculate their design score, designers must multiply the value shown next to the box selected in each category. The score is determined through equation 1:

$$(1) \qquad Inspectability\ Score = TF \times CoI \times ICI$$

If the score from any one category is equal to zero, the inspectability score will drop to zero. If designers fail to keep any of the considerations in mind, it could greatly diminish the inspectability of components. Maximizing the scores in two columns but scoring a zero in any column may still render a part un-inspectable. Once the worksheet was established, it was necessary to study how consideration of inspectability constraints early in the design process affects downstream design outcomes. This was accomplished via an in-depth design case study.

3.3 Pilot Test of DfI

With a tool such as the DfI worksheet, introduction to designers may lead to significant changes in design outcome. When the DfAM worksheet was introduced to a lab featuring Makerbot printer, it was found that print failures reduced by 83% [62]. With the complexity of information covered in the DfI worksheet, it was necessary to run an initial test to see what effect the introduction of DfI considerations had on deign outcomes. If results were significant or had a large effect size, it would warrant further study with a larger sample.

3.3.1 Pilot Test Methods

To test the effect of DfI on downstream design outcomes, engineers and designers were recruited from The Pennsylvania State University. Participants for this study were recruited through purposeful [99] and snowball [100] sampling methods leveraging various engineering groups with activities related to AM. Recruitment for this in-person design study continued until social distancing protocols were put in place due to the COVID-19 pandemic and the investigators halted experimentation for safety of participants and facilitators. In total, 12 engineering graduate and undergraduate students were selected based on their familiarity and expertise with AM and their proficiency using Autodesk Fusion 360. Students' ages ranged from 20 to 27, with an average age of 23.6; 10 students identified as male and 2 identified as female. On average, participants had 4.8 years of experience with AM and 6.9 years of experience with CAD.

Participants were randomly sorted into control and experimental groups. Participants in the control group were not exposed to DfI methods, while participants in the experimental group were instructed to use the DfI worksheet. Participants in both groups followed the same timeline, with five minutes for introduction, ten minutes to complete a pre-survey, fifteen minutes for an inspection task, forty-five minutes for the design challenge, and ten minutes for a post-task survey. In accordance with the Institutional Review Board, all participants were introduced to the purpose of the study and provided an overview of the experiment at the start of the study. Participants were informed that their participation was voluntary, and all data would be kept confidential; written consent to participate in the research was collected. Following this, participants filled out a pre-survey assessing familiarity with AM and CAD. The pre-survey included questions about demographic data as well as experience in DfAM, CAD, and QA/QC. Demographic data included self-identified gender, ethnicity, and professional title. Data on DfAM experience included years of experience with AM and AM technologies with which they are proficient. Data on CAD experience included years of experience with

AM and CAD packages with which they are proficient. Data on QA/QC included all NDT methods with which they have experience.

Following the pre-survey all participants were provided with the design prompt. Participants were told “the mass of the bracket must be reduced by at least 50% and fulfill all requirements on the provided ‘Specifications and Loading Conditions’.” This prompt was adapted from GE Jet Engine Bracket Challenge [101], more commonly known as the GE Bracket challenge. The GE Bracket challenge was an open competition sponsored by GE to reduce the weight of an engine bracket while maintaining strength, resulting in a design repository of 635 designs. The GE Bracket challenge was chosen by the research team as it is a well-scoped design challenge and would enable the research team to compare designs collected in the experiment to a large design repository in future work.

Before in-person testing was halted, 4 participants in the control group and 8 participants in the experimental group had completed all design tasks. We acknowledge the small sample size as a limitation of the work, however we highlight the aim of this preliminary study was to understand what if any effects DfI constraints may have on downstream design outcomes. Additionally, we highlight that for each participant over 80 minutes of audio and video recording was captured, providing rich data regarding design decisions and actions. Participants in the experimental group were given a 15-minute inspection task and were tasked with assessing the model, shown in Figure 3-5 (TOP), for inspectability using the Design for Inspectability using Pulse-Echo Ultrasonic Testing Worksheet. The purpose of this training task was to ensure participants were familiar with the worksheet and were able to successfully use the CAD program. Participants in the control group were tasked with a similar 15-minute inspection task to minimize incubation effects [102]. Their task was to verify that a CAD model matched a provided engineering drawing, shown in Figure 3-5 (BOTTOM).

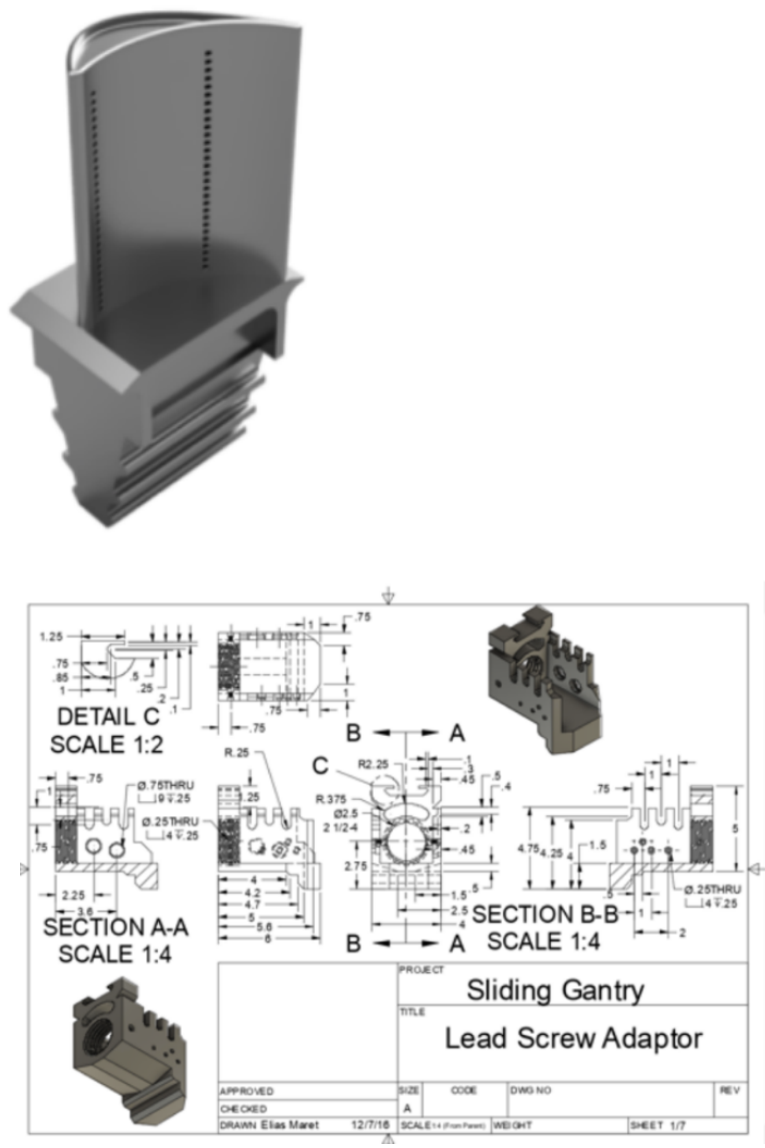


Figure 3-5. Models used in the inspection by participants in (TOP) experimental and (BOTTOM) control groups

3.4 Assessing Design Outcomes of Design Study

In order to understand the effect of DfI considerations on downstream design outcomes, mass reduction, strength, and inspectability were used to evaluate final parts produced in the experiment. Two models from the experimental group included non-manifold geometry which prevented convergence of static structural models and would prevent proper build using AM [103,104]. These models were removed from this portion of analysis. One model from the control group was not altered from the original design. Instead, this designer spent all allotted time simulating load conditions. While the bracket was analyzed using static structural analysis, results from the designer were removed as an outlier.

3.4.1 Mass Reduction

The average reduction of mass in the experimental group was 33 percent, while the average reduction of mass in the control group was 52 percent. A Cohen's d with a Hedges g correction [105] to account for small samples was calculated to be >.99 indicating a large effect size. In other words, our results suggest that the difference between groups was trending towards significance and given larger sample sizes a significant difference in average mass reduction would be observed between the groups. This result suggests that restrictive DfI heuristics may limit designer ability to utilize specific advantages of AM, in this case the ability to produce low-weight components.

3.4.2 Part Strength

Strength was assessed by determining the maximum stress in each model under the load conditions shown in Figure 3-6. A static structural simulation was conducted in ANSYS 2019 R3 assuming Ti-6Al-4V properties for the brackets, as specified in the GE

Jet Engine Bracket challenge [78,106]. For each of the designs analyzed, all four load conditions were simulated, the load condition with the highest von Mises stress was identified, and the maximum stress in that load condition was recorded as σ_{max}. Factor of Safety (FoS) was calculated using equation 1, where σ_Y represents the yield strength, 903 MPa as specified by the GE Jet Engine Bracket challenge [101], and σ_{max} represents the maximum von Mises stress.

$$FoS = \frac{\sigma_Y}{\sigma_{max}} \qquad \text{eq.1}$$

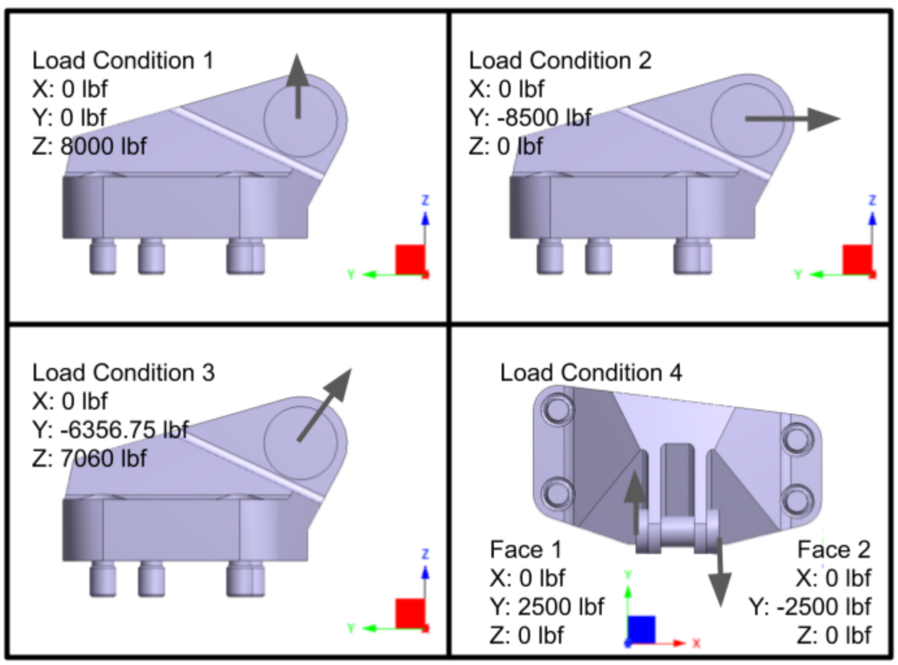


Figure 3-6. Loading conditions provided to participants and used in FEA analysis

The average maximum stress in experimental group models was 751 MPa and the average stress in control group models was 1380 MPa. A Cohen's d with a Hedges g correction [105] to account for small and unequal sample sizes was calculated to be <.99, indicating a large effect size. All four models created by the experimental group had a

Factor of Safety (FoS) greater than one. One of the three models created by the control group had a FoS greater than one. While results are not statistically significant due to the limited sample size, the Cohen's d reveal a large effect of DfI on strength. Designers in the experimental group had a higher factor of safety, suggesting that they were more conservative in their removal of material. This result is backed up by the lower reduction of mass, and suggests that the addition of the new constraint, inspectability of the component, may hinder a designer's use of opportunities unique to DfAM, such as creation of lightweight high-strength structures. However, we note that participants in the control group created geometries that would have failed in use. The restrictive nature of DfI constraints, thus, may be beneficial in some design cases. This phenomenon warrants further study.

3.4.3 Inspectability

Inspectability of each component was determined through a simulated Probability of Detection (PoD) assessment. First, a defect was added to a point in each design likely to lead to failure. Next, ultrasonic waves traveling through the part were simulated to mimic Pulse-Echo Ultrasonic (PEU) testing. Finally, a validated PoD software was used to determine the PoD for each design. Directly comparing the PoD of each design allowed for a quantitative comparison of inspectability.

Static structural simulations in ANSYS 2019 R3 were used to select defect locations. Candidate locations were internal points at least 1.27 mm from the surface of the part where stress was at least seventy-five percent of the maximum stress. Points were selected by visual inspection, as shown in Figure 3-7. Five of the designs were inspected by two researchers to ensure agreement and consistency, and all remaining designs were inspected by the author.

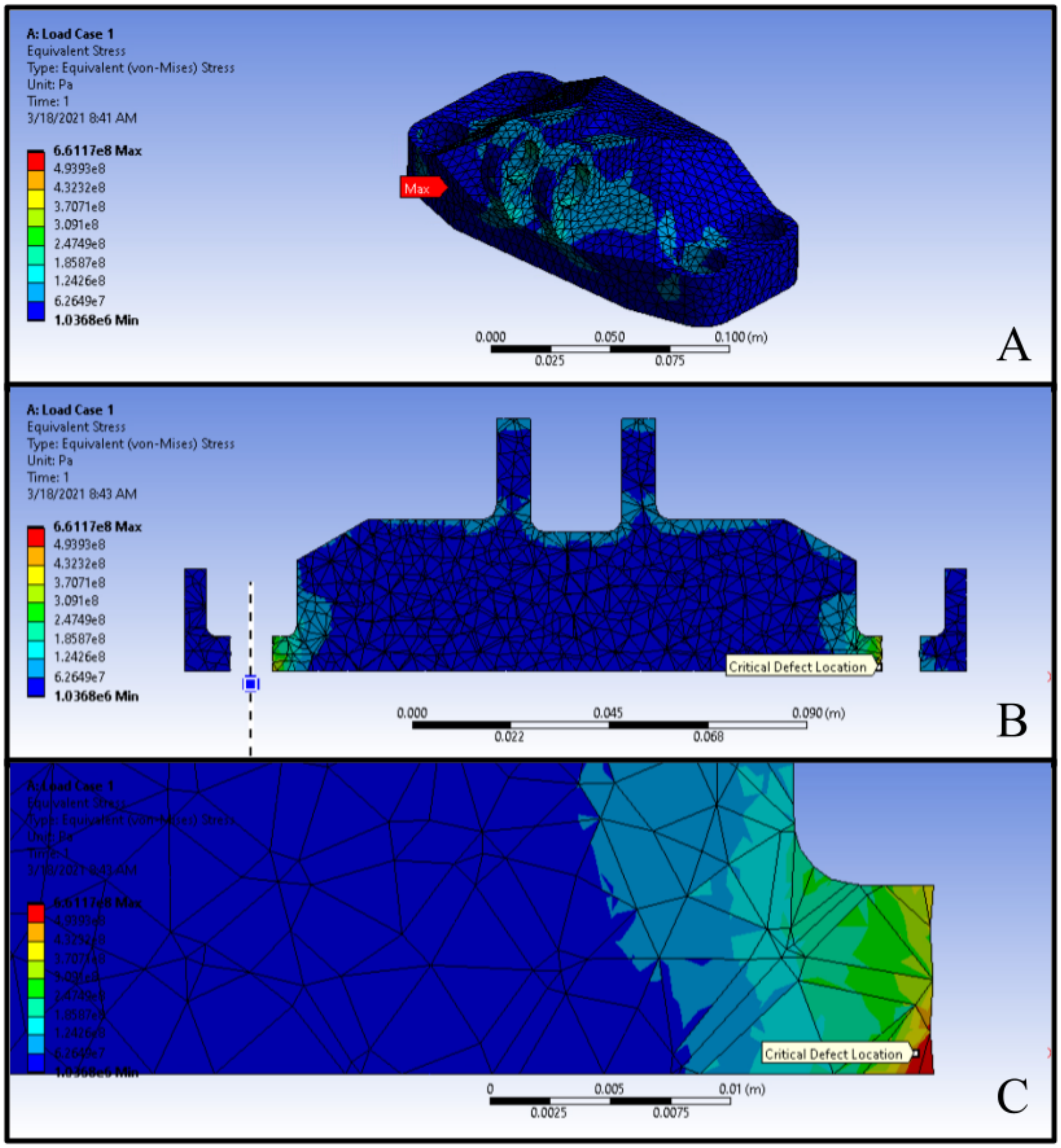


Figure 3-7. Process of visual inspection for identification of location of critical defect. Included is (A) identification of point of maximum stress, (B) identification of critical defect location using cross-sectional cut plane, and (C) visualization of defect and surrounding part geometry for dynamic explicit simulation

Calculation of $a_{90/95}$ was performed using simulation of ultrasonic wave propagation. Ultrasound simulations were performed using dynamic explicit simulation in the finite element analysis software Abaqus 2018. The geometry simulated for each design was taken directly from identification of critical defect locations, shown in Figure 7C. For detection simulations, only a 2D cross-sectional area was taken for each design. The dimension in and out of the cross-sectional area plane is large so the plane-strain and 2D assumption are appropriate. Because 3-dimensional simulations are computationally intensive, the added accuracy of the third dimensions does not justify the added computational expense for this application. Each geometrical configuration was created and given the Ti-6Al-4V material properties. For each geometrical simulation, a simulation was run that included no defect, followed by simulations with defect sizes from 0.1 - 0.7mm, with an interval of 0.1mm, resulting in eight simulations per design. The simulations were run for 2 microseconds with a time step of 2 nanoseconds. The time step is sufficiently small, following the metric such that no disturbance travels over a mesh element in under one time-step.

A longitudinal wave was generated by placing concentrated forces perpendicular to the cross-section's edge with 10 MHz 2-cycle tone burst displacements along a 6.35 mm segment, analogous to a pulse-echo setup. Each simulation was meshed using free CPE3 elements with a size of 50 microns. This element size is in accordance with the literature, recommending that element size be at least 10 nodes per wavelength [107]. Simulations were performed on the Pennsylvania State University's Institute for Computational and Data Sciences' Roar supercomputer. The high-amplitude excitation wave shown in Figure 3-8A represents the ultrasonic transducer putting energy into the component to send a pulse into the component. Displacement histories were collected along the excitation segment and summed to generate one received signal, as shown in Figure 3-8B. The reflection off the defect, shown in Figure 3-8B occurs after the ultrasonic wave encountered the defect, reflected off and returned to the transducer, where it can be measured. The amplitude of the wave is associated with the size of the defect while the time it takes for the wave to return relates to the distance of the defect from the transducer. The final pulse in the signal corresponds with the reflection from the surface opposite the transducer.

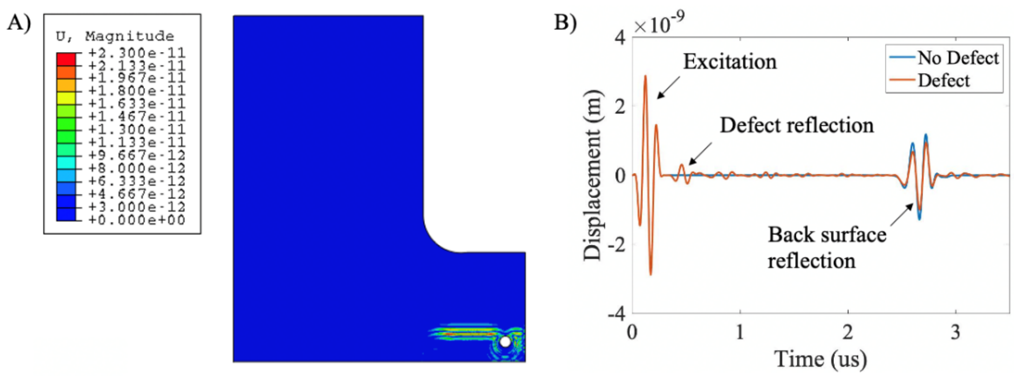


Figure 3-8. Results of ultrasonic wave propagation test for one participant, (A) with no defect introduced and (B) with a 0.7 mm spherical defect introduced

In order to simulate a realistic pulse-echo ultrasonic inspection, Gaussian noise was added with a signal to noise (SNR) ratio of 10 [78][108] using MATLAB R2018b. Ten iterations of noise addition were conducted per simulation to calculate PoD. The peak amplitude in the reflection off the defect was recorded for each simulation to calculate $a_{90/95}$ using software mh1823-POD [78,79,109]. More information on the equations used to calculate $a_{90/95}$ can be found in [109]. The typical output for a design can be seen in Figure 3-9, with the size of flaw shown in millimeters on the horizontal axis and the Probability of Detection (PoD) shown on the vertical axis. The solid black line in the center of the graph represents the PoD curve as calculated by mh1823-POD. The dotted curves to the left and the right of the PoD curve are the 5% and 95% confidence intervals, respectively. The flaw size with 90% PoD on the 95% confidence interval is the $a_{90/95}$. While the confidence interval and PoD threshold can be raised to meet quality goals, the $a_{90/95}$ is ubiquitous in determining efficacy of NDT [78].

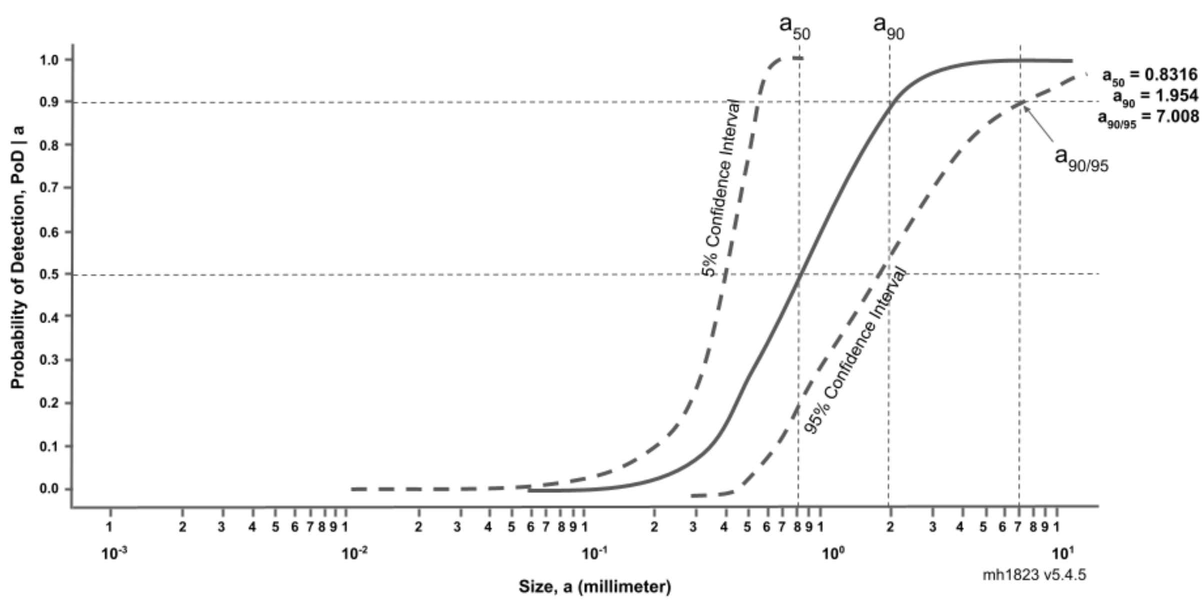


Figure 3-9. Results of $a_{90/95}$ calculation using mh-1823-POD software.

The average $a_{90/95}$ for the control group was 3.94 millimeters and the average for the experimental group was 2.73 millimeters. A Cohen's d with a Hedges g correction [105] to account for small sample sizes was calculated to be .631, indicating a large effect size. While results are not statistically significant due to the limited sample size, they suggest that designers may produce more inspectable designs when using the DfI worksheet. This initial test suggests that either the problem framing, telling designers that parts must be inspectable using PEU, or the tool provided, the DfI worksheet, may help designers to produce designs which are more easily inspected with PEU.

3.5 Chapter Summary

Based on calls from professional societies like AMSC, the DfI framework was created as a way to help designers consider QA/QC early in the design process. Open and axial coding of literature was used to collect major and minor factors affecting PoD using UT. Heuristics were developed to help designers increase the inspectability of components. The DfI worksheet was created to test what effect introducing DfI considerations would have on designers and design outcomes. After three rounds of major revisions, the DfI worksheet was incorporated into a pilot test. Designers and engineers from The Pennsylvania State University participated in a controlled design study, which consisted of an inspection task and a redesign task. In the inspection task, participants in the experimental group were provided the DfI worksheet and asked to evaluate the inspectability of a part, while participants in the control group were given a neutral task. In the redesign task, all participants redesigned a component to reduce its mass by 50% while meeting all specifications and preventing yield under mechanical loading. The experimental group had one additional constraint, that the component must be inspectable using PEU. While differences in mass were not significant, designs created by participants exposed to DfI considerations were heavier with a large effect size observed. This suggests that introducing DfI considerations may have led participants to be more conservative with their material removal. The large effect size suggests this result warrants testing with a larger sample size. Further, the peak stress was lower in components designed by participants exposed to DfI considerations. While not significant, the large effect size suggests this result warrants testing with a larger sample size. Finally, the $a_{90/95}$ was lower in components created by participants exposed to DfI considerations, meaning those components were more inspectable. The large effect size observed indicates that with larger samples significant differences between groups may be observed. As such, additional testing was conducted to understand more clearly the effect of DfI on end designs. Additionally, the effect DfI may have on designer behaviors and strategies was also investigated. These studies are reviewed in Chapters 4 and 5 respectively.

Chapter 4

Effect of DfI on Design Outcomes

When introducing a novel DfX framework or a design tool, it is important to understand what effect this will have on design outcomes, in particular those outcomes the framework seeks to change. When Booth et al. introduced the DfAM worksheet, rate of print failures was used to determine the efficacy of restrictive considerations [62]. This type of information can be used to revise design tools or frameworks, ensuring they help designers to achieve better outcomes. In addition, such data helps to encourage the adoption of DfX frameworks in industry by building a foundational understanding of the framework's effects. Increased efficiency and decreased manufacturing costs have led to widespread adoption of DfA principles [63,110]. Before DfI can be considered a viable tool for engineers and designers in industry, it is important that the effect of DfI considerations on design outcomes be understood.

In pursuit of RQ1, *What effects do DfI considerations have on design outcomes, including inspectability*, a controlled study was conducted with 20 practicing designers. Half of these designers were exposed to the DfI framework during a 15-minute inspection task, and the remaining designers participated in a control task. Designers were tasked with redesigning a part so that its mass was reduced by fifty percent, was manufacturable using AM, and did not fail under four provided loading conditions. Those participants who were exposed to DfI were given an added constraint, that the part must be inspectable using PEU.

4.1 Experimental Design

Participants first completed a pre-study survey via Qualtrics provided in email. This survey was used to inform participants about the study, ensure inclusion criteria were met, generate an anonymous user id used for storing all collected information, and collect information such as age, gender, their experience with CAD, their experience with AM, and their experience with NDT. On page 6 of the survey, anyone who would like to continue to the design portion of the study were provided a link to a second Qualtrics survey, where they could provide an email used to schedule the design task. While less convenient for participants to fill in two surveys, directing participants to the second survey to provide an email ensured that there was no identifying information associated with pre-study survey data, in accordance with IRB protocol. Participants then scheduled a time for the virtual experiment via zoom by email correspondence through the address provided.

Participants were separated into control and experimental groups. To ensure that members in the experimental group were familiar with the DfI Worksheet, they participated in a 15-minute inspection task, and participants in the control group participated in a similar, neutral 15-minute task. Following the inspection task, designers in each group spent 45 minutes redesigning a part. To gather data on mass reduction, stress, and inspectability, all designs generated were saved and underwent static structural analysis followed by simulation of ultrasonic wave propagation. A series of non-parametric tests were used to compare the performance of designs generated by participants in the control and experimental groups.

Considerable changes to the testing procedure described in Chapter 3 were implemented before testing, in order to comply with COVID-19 Social Distancing protocol. First, and most importantly, the procedure was adapted to be performed virtually rather than in-person.

4.2 Participants

Participants were recruited from the Additive Manufacturing, Mechanical Engineering, and Engineering Design graduate programs at The Pennsylvania State University. Participants for this study were recruited through purposeful [99] and snowball [100] sampling methods leveraging various engineering groups with activities related to AM. Participant ages ranged from 20-58 years of age. Nineteen participants identified as male, and one participant identified as female. One participant identified as Hispanic, Latino, or Spanish origin, one as Middle-Eastern or North African, one as Asian, one as white and Asian, and sixteen as white.

The average age of participants in the experimental group was 31.7 years and in the control group was 27.4 years. There was homogeneity of variances for the age of participants in control and experimental groups, as assessed by Levene's test for equality of variances ($p = .174$). *There was no statistically significant difference in age between control and experimental groups,* $t(18) = .912$, $p = .374$. The average number of years of experience with AM was 3.5 years in the control group, and 2.9 years in the experimental group, as shown in Figure 4-1. There was homogeneity of variances for the years of experience with AM of participants in control and experimental groups, as assessed by Levene's test for equality of variances (p = .820). *There was no statistically significant difference in years of experience with AM between control and experimental groups, t(18) = .639, p = .531.*

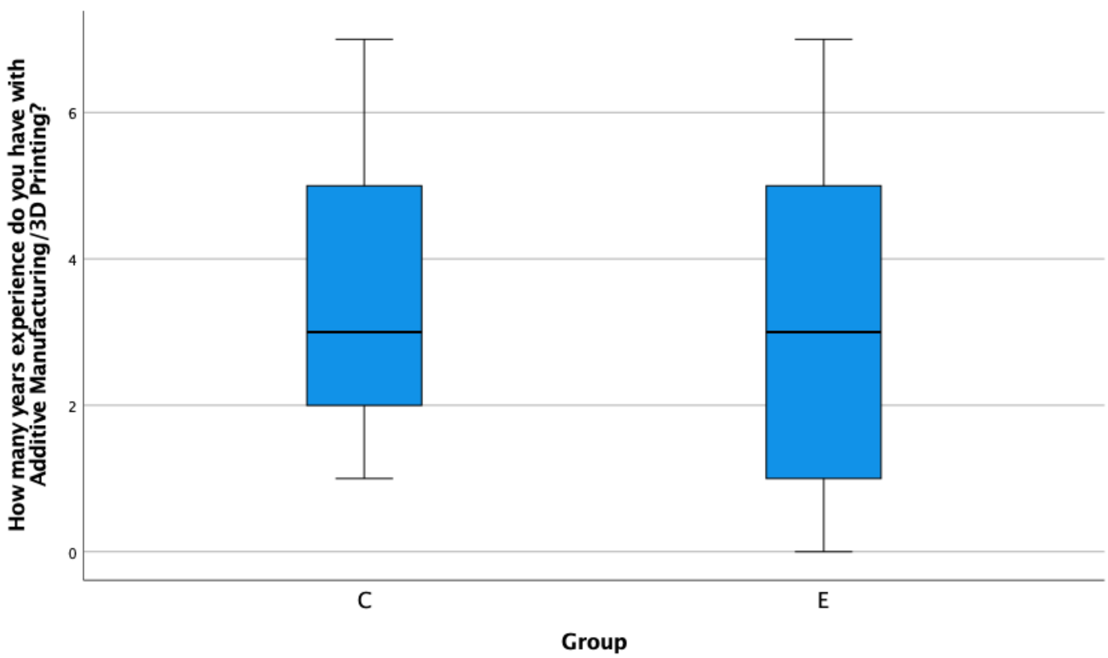


Figure 4-1. Years of experience with AM for the Control Group (C) and Experimental Group (E)

Members of the experimental and control groups had similar years of experience with CAD. The experience was similar amongst members in the control group, 6.2 years, than members in the experimental group, 4.4 years, as shown in Figure 4-2. There was homogeneity of variances for the years of experience with CAD of participants in control and experimental groups, as assessed by Levene's test for equality of variances (p = .253). *There was no statistically significant difference in age between control and experimental groups, t(18) = .999, p = .331.* Thus, control and experimental groups had similar prior experience in CAD, AM, and were of similar ages. We do not expect participants' prior experiences to effect results.

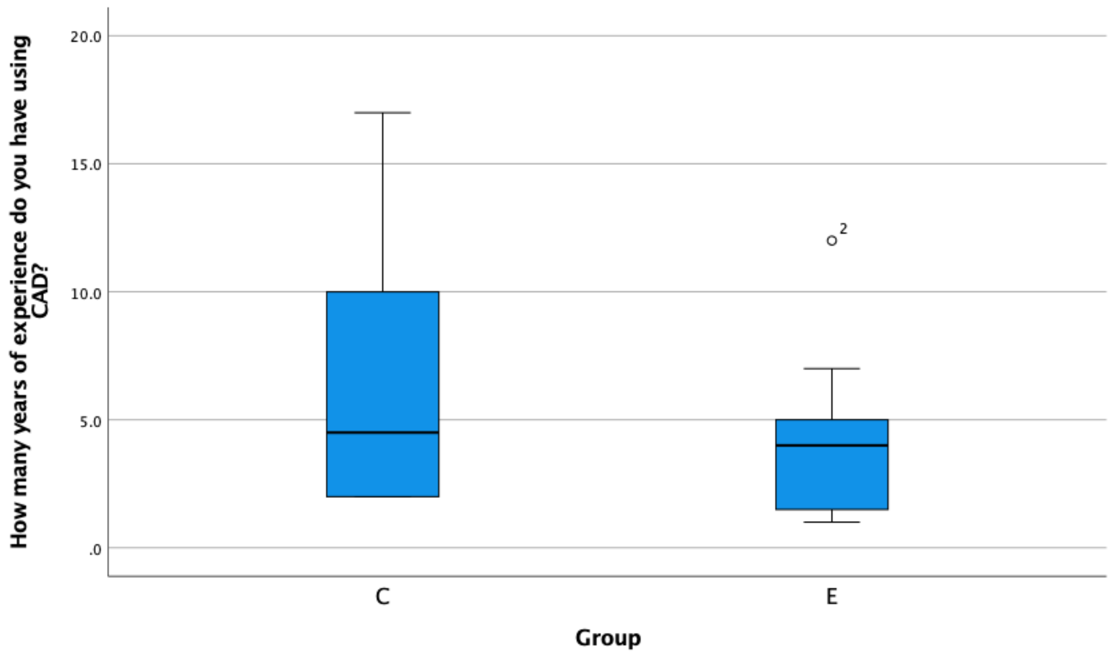


Figure 4-2. Years experience with CAD for the Control Group (C) and Experimental Group (E)

4.3 Inspection and Redesign Tasks

Participants in both groups followed the same timeline, with five minutes for introduction, fifteen minutes for an inspection task, five minutes for a NASA TLX survey, forty-five minutes for the design challenge, and five minutes for a post-task survey. In accordance with the Institutional Review Board, all participants were introduced to the purpose of the study and provided an overview of the experiment at the start of the study. Participants were informed that their participation was voluntary, and all data would be kept confidential; written consent to participate in the research was collected.

Participants in the experimental group were given a 15-minute inspection task and were tasked with assessing the model, shown in Figure 4-3 (TOP), for inspectability using the Design for Inspectability using Pulse-Echo Ultrasonic Testing Worksheet. The purpose of this training task was to ensure participants were familiar with the worksheet and were able to successfully use the CAD program. Participants in the control group were tasked with a similar 15-minute inspection task [102]. Their task was to verify that the same CAD model matched a provided engineering drawing, shown in Figure 4-3 (BOTTOM). In the pilot study outlined in Chapter 3 participants in the control and experimental groups reviewed different design components for the inspection task. To minimize the effect any difference in materials provided to participants may have on the experiment, one model was created that could be used by the control and experimental groups. In other words, while the control and experimental groups saw different geometries in the procedure listed in Chapter 3, the experimental and control groups saw the same model during the inspection task during this iteration of the design study. While no evidence was seen in the first design study to suggest that a difference in models primed the participants or affected design outcomes, this important change was done out of an abundance of caution.

Following the inspection task, designers were given five minutes to practice using OnShape to change an imported geometry. Participants were told to modify the design provided in the inspection task using any of the tools provided in OnShape. OnShape was selected because of its function as an online CAD tool, ideal for work with Covid-19 safety protocols, but its use was not widespread at The Pennsylvania State University. Although all participants had experience with CAD, experience with OnShape was not required for participation in this task. This limitation is discussed further in Chapter 6.

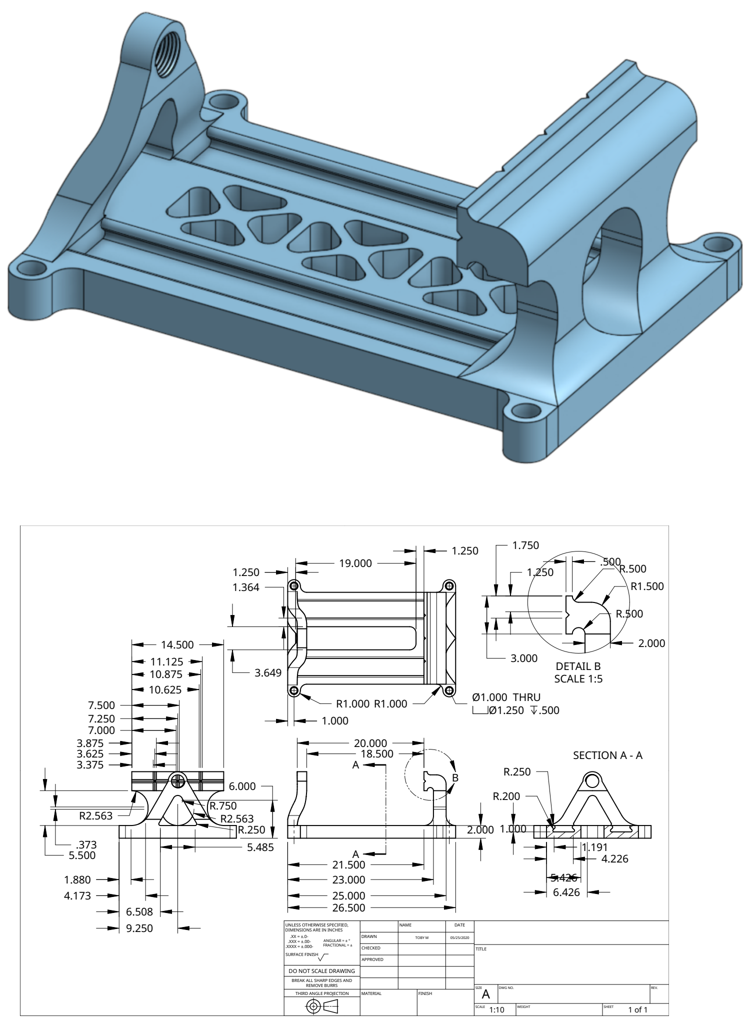


Figure 4-3. The (TOP) models used in the inspection task by participants in both groups experimental and (BOTTOM) drawing used by the control group

After the inspection task was completed, participants were instructed to modify the component shown in Figure 4-4A. Participants were instructed to reduce the mass of the bracket by 50%, ensure the component met specifications outlined by loading conditions (Figure 4-4B), and was readily producible via metal AM. Participants in the experimental group were given one additional constraint, to ensure their design was inspectable using Pulse-Echo Ultrasonic Testing.

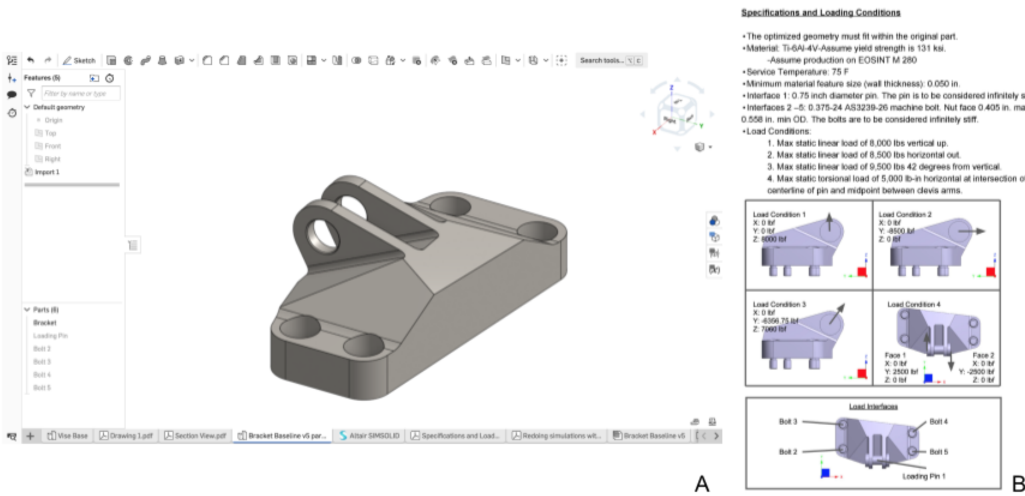


Figure 4-4. The (A) part provided in OnShape for participants to redesign and (B) specifications to be met during the redesign

Participants were provided with a copy of Altair Simsolid where all four loading conditions were prepared and solved. In addition, participants received written instructions on how to redo simulations using their own designs, to ensure participants were able to iteratively test the strength of design concepts.

4.4 Effect of Inspectability on Downstream Design Outcomes

The final designs created by designers were saved for analysis of design outcomes, specifically strength, volume change, and inspectability. Instead of mass, change in volume was calculated since the density was assumed to be constant and volume can be calculated directly from almost all file formats. Difference in volume change by designers in the experimental and control groups were compared using a Mann-Whitney U Test, a test not sensitive to outliers or non-normally distributed data [111]. The peak stress was determined for each deign under all four loading conditions. Difference in peak stress in components by designers in the experimental and control groups were compared using a Mann-Whitney U Test. Finally, $a_{90/95}$ of critical features was determined using static structural analysis, ultrasonic wave propagation simulation and MIL-HDBK-1823A software. After removing significant outliers, a t-test was run to determine differences in inspectability of components by designers exposed to DfI considerations and designers in the control group.

4.4.1 Change in Volume

A Mann-Whitney U test was run to determine if there were differences in volume reduction between experimental and control groups. The median values of volume were .4614 and .4934 for the experimental and control groups, respectively. Distributions of the volume change for the control and experimental groups were similar, as assessed by visual inspection. Median volume change was not statistically significantly different between experimental and control groups, $U = 45$, $z = -.378$, $p = .739$, using an exact sampling distribution for U (Dineen & Blakesley, 1973), as shown in Figure 4-5. Cohen's d was calculated as 0.257, indicating a small effect size.

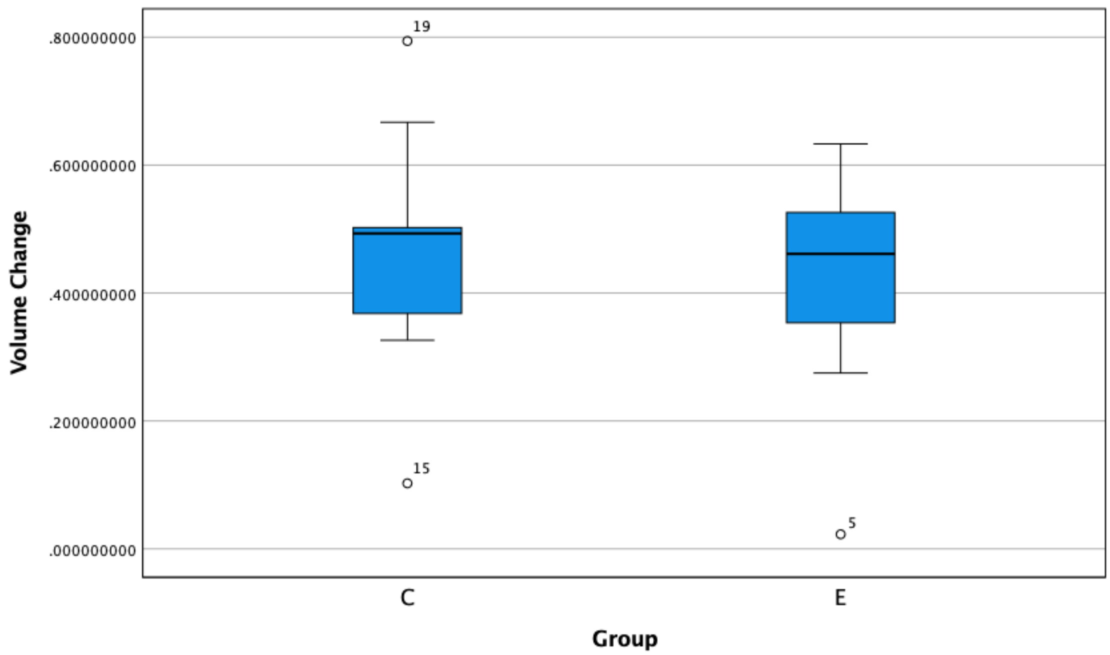


Figure 4-5. Volume change for the Control Group (C) and Experimental Group (E)

There were three observed outliers, one from the control and experimental groups. The years of experience in CAD and AM were not inadequate, and no technical difficulties were observed during the testing protocols. The Mann-Whitney U Test is not sensitive to outliers, and it is best practice to leave in outliers unless an error in data collection can be identified [111]. For these reasons, outliers were not removed during statistical analysis.

4.4.2 Strength of Designs

Strength was assessed by determining the maximum stress in each model under the load conditions shown in Figure 6. A static structural simulation was conducted in ANSYS 2019 R3 assuming Ti-6Al-4V properties for the brackets, as specified in the GE Jet Engine Bracket challenge [78,106]. For each of the designs analyzed, all four load conditions were simulated and the maximum stress in each load condition was recorded as σ_{max}.

The first loading condition consisted of an 8000-pound force applied vertically to the pin, as shown in Figure 4-6.

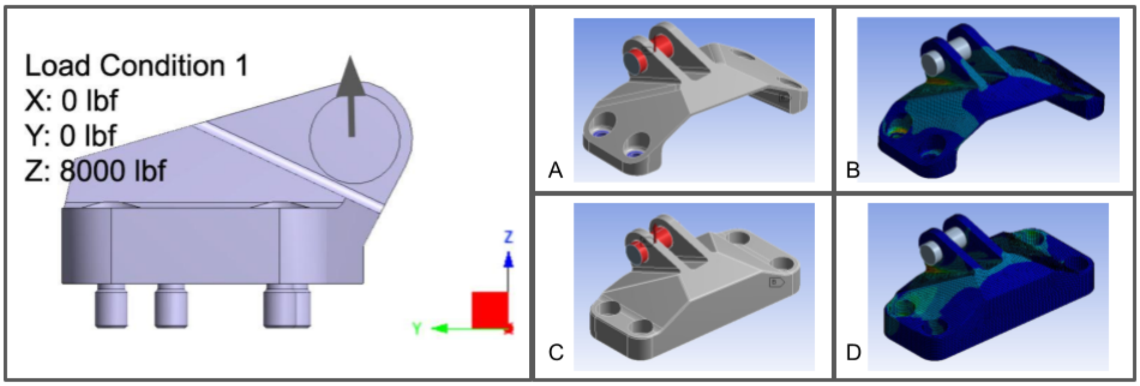


Figure 4-6. First loading condition, shown on the left, appears as it was presented to participants. A design chosen randomly from the experimental group (A) simulated in ANSYS (B). A design chosen randomly from the control group (C) simulated in ANSYS (D).

A Mann-Whitney U test was run to determine if there were differences in maximum stress between experimental and control groups in load condition 1. The median values of maximum stress were 941460000 Pa and 89171000 for the experimental and control groups, as seen in Figure 4-7. Distributions of the maximum stress for the control and experimental groups were similar, as assessed by visual inspection. Median stress was not statistically significantly different between experimental and control groups, U = 53.5, z = .265, p = .796, using an exact sampling distribution for U (Dineen & Blakesley, 1973). Cohen's d was calculated to be 0.227, indicating a small effect size.

There were two observed outliers, one from the control and experimental groups. The years of experience in CAD and AM were not inadequate, and no technical difficulties were observed during the testing protocols. For these reasons, outliers were not removed during statistical analysis.

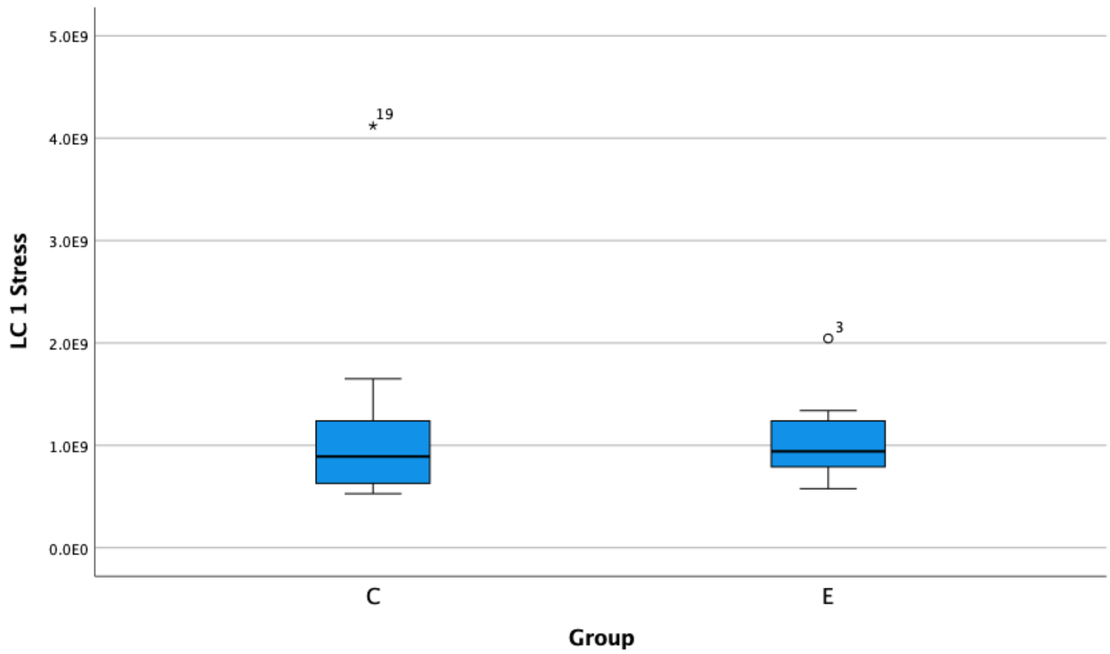


Figure 4-7. Maximum stress observed in Load Condition 1 for the Control Group (C) and Experimental Group (E)

The second loading condition consisted of an 8500-pound force applied horizontally to the pin, as shown in Figure 4-8.

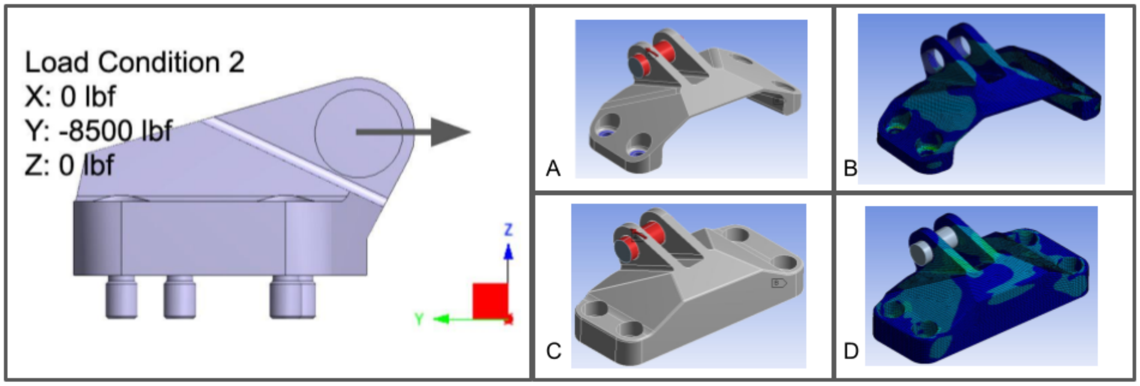


Figure 4-8. Second loading condition, shown on the left, appears as it was presented to participants. A design chosen randomly from the experimental group (A) simulated in ANSYS (B). A design chosen randomly from the control group (C) simulated in ANSYS (D).

A Mann-Whitney U test was run to determine if there were differences in maximum stress between experimental and control groups in load condition 2. The median values of maximum stress were 770385000 Pa and 761565000Pa for the experimental and control groups, as seen in Figure 19. Distributions of the percent mass change for the experimental and control groups were similar, as assessed by visual inspection. *Median stress was not statistically significantly different between experimental and control groups, $U = 49$, $z = -.076$, $p = .971$, using an exact sampling distribution for U (Dineen & Blakesley, 1973).* Cohen's d was calculated to be 0.102, indicating a small effect size.

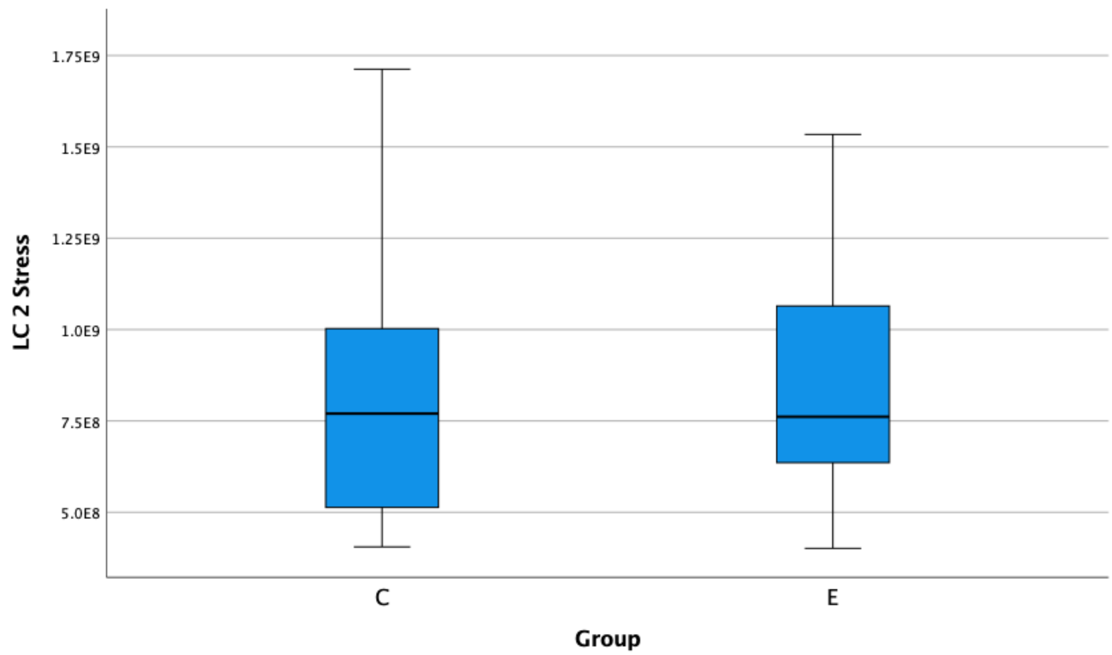


Figure 4-9. Maximum stress observed in Load Condition 2 for the Control Group (C) and Experimental Group (E)

The third loading condition consisted of a 9500-pound force applied to the pin at an angle 42 degrees from vertical, as shown in Figure 4-10. For ease of simulation in Altair Simsolid, the force was presented in component form rather than as a vector.

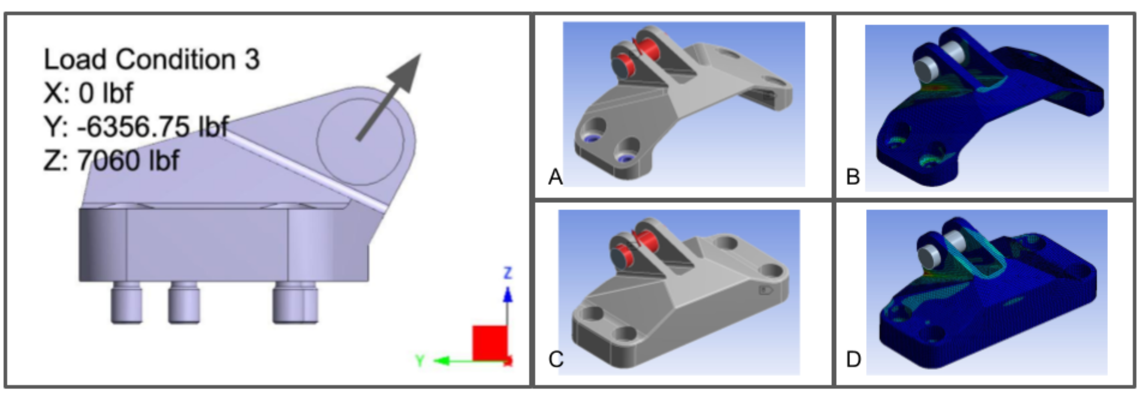


Figure 4-10. Third loading condition, shown on the left, appears as it was presented to participants. A design chosen randomly from the experimental group (A) simulated in ANSYS (B). A design chosen randomly from the control group (C) simulated in ANSYS (D).

A Mann-Whitney U test was run to determine if there were differences in maximum stress between experimental and control groups in load condition 3. The median values of maximum stress were 637155000 Pa and 696335000 Pa for the control and experimental groups, as shown in Figure 4-11. Distributions of the maximum stress were similar for experimental and control groups, as assessed by visual inspection. *Median stress was not statistically significantly different between experimental and control groups, $U = 57$, $z = .529$, $p = .631$, using an exact sampling distribution for U (Dineen & Blakesley, 1973).* Cohen's d was calculated to be 0.314, indicating a small effect size.

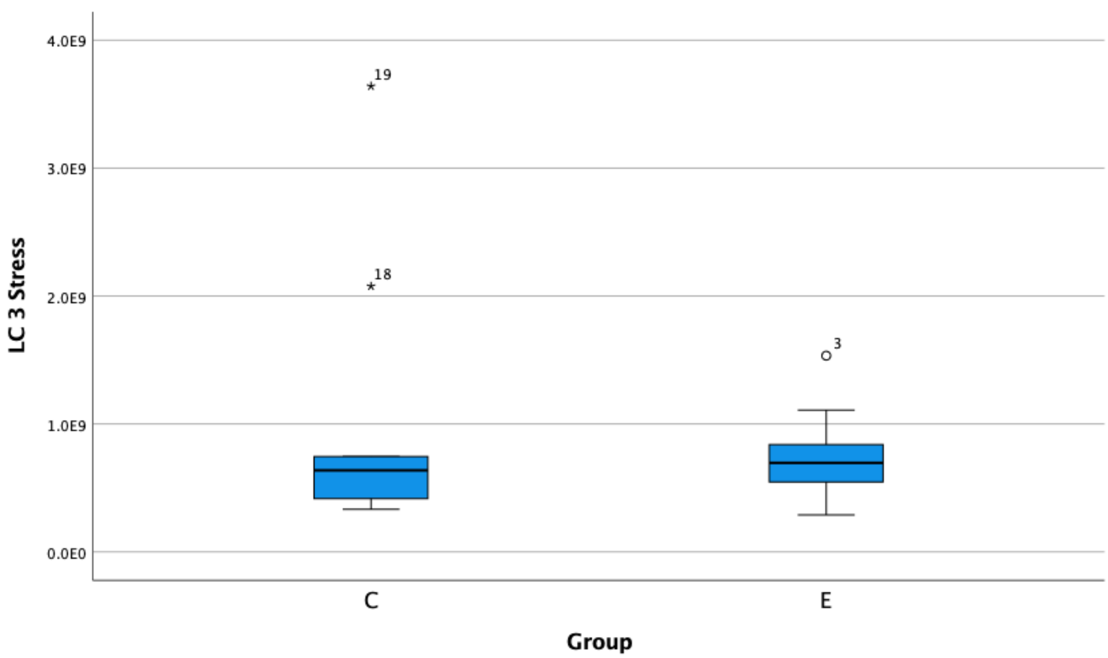


Figure 4-11. Maximum stress observed in Load Condition 3 for the Control Group (C) and Experimental Group (E)

The fourth loading condition consisted of a 5000-pound-inch torsional force applied to the pin at its centroid, as shown in Figure 4-12.

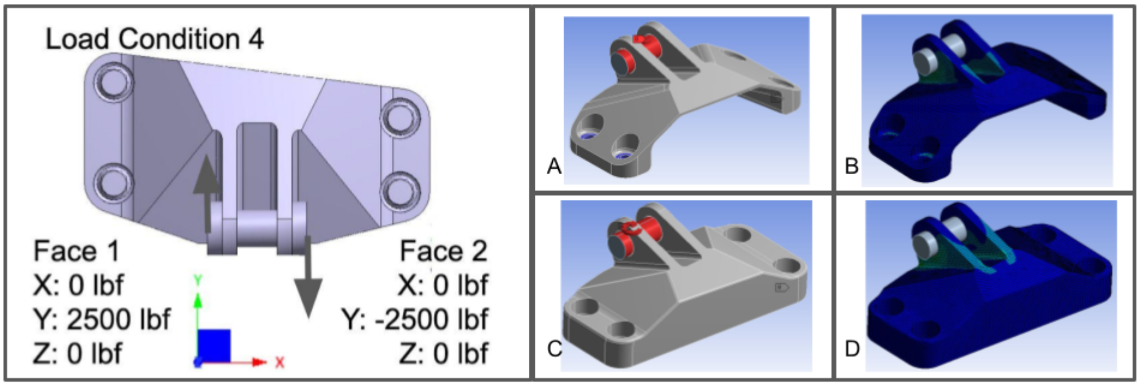


Figure 4-12. Fourth loading condition, shown on the left, appears as it was presented to participants. A design chosen randomly from the experimental group (A) simulated in ANSYS (B). A design chosen randomly from the control group (C) simulated in ANSYS (D).

A Mann-Whitney U test was run to determine if there were differences in maximum stress between experimental and control groups in load condition 4. The median values of maximum stress were 409930000 Pa and 398790000 Pa for the experimental and control groups, respectively. Distributions of the maximum stress for the experimental and control groups were similar, as shown in Figure 4-13. Median stress was not statistically significantly different between experimental and control groups, $U = 39$, $z = -.832$, $p = .436$, using an exact sampling distribution for U (Dineen & Blakesley, 1973). Due to the presence of outliers, Glass's delta was used selected as a non-parametric test of effect size. The value of Glass's d was 0.237, indicating a small effect size.

There were three observed outliers, two from the control and one from the experimental group. The years of experience in CAD and AM were not inadequate, and no technical difficulties were observed during the testing protocols. For these reasons, outliers were not removed during statistical analysis.

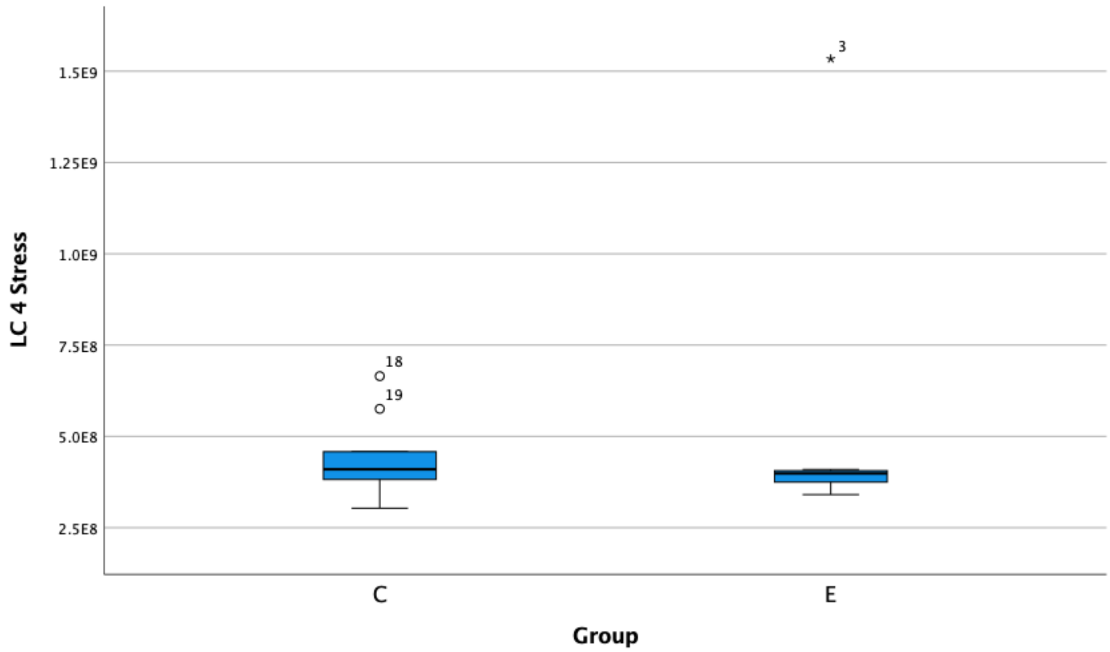


Figure 4-13. Maximum stress observed in Load Condition 4 for the Control Group (C) and Experimental Group (E)

There was no significant difference in the maximum stress for any load condition. This means that the addition of DfI considerations into the design process did not significantly change the ability of designers to reach a favorable design outcome. However, there are medium effect sizes observed for load conditions 1&3. When applying these loads to the original, unedited bracket these load conditions experienced the highest stress. It is possible that the addition of DfI considerations at this stage in the design process may impede designer ability to maintain strength in their designs, an effect that is more pronounced in parts closer to yield. Further study is needed to determine if this result is significant with larger sample sizes, discussed further in Chapter 6.

4.4.3 Design Inspectability

Inspectability of each component was determined through a simulated Probability of Detection (PoD) assessment. First, a defect was added to a point in each design likely to lead to failure. Next, ultrasonic waves traveling through the part were simulated to mimic Pulse-Echo Ultrasonic (PEU) testing. Finally, a validated PoD software was used to determine the PoD for each design. Directly comparing the PoD of each design allowed for a quantitative comparison of inspectability.

Static structural simulations in ANSYS 2019 R3 were used to select defect locations. Candidate locations were internal points at least 1.27 mm from the surface of the part where stress was at least fifty percent of the maximum stress. Two models, one from the experimental group and one from the control group, were identified as having features less than the minimum feature size, 1.27 mm. There figures are shown in Figure 4-14. These models feature infinitely thin features which act as stress risers. It was not possible to identify points which met all criteria decided for a defect location, and these points were excluded from further analysis.

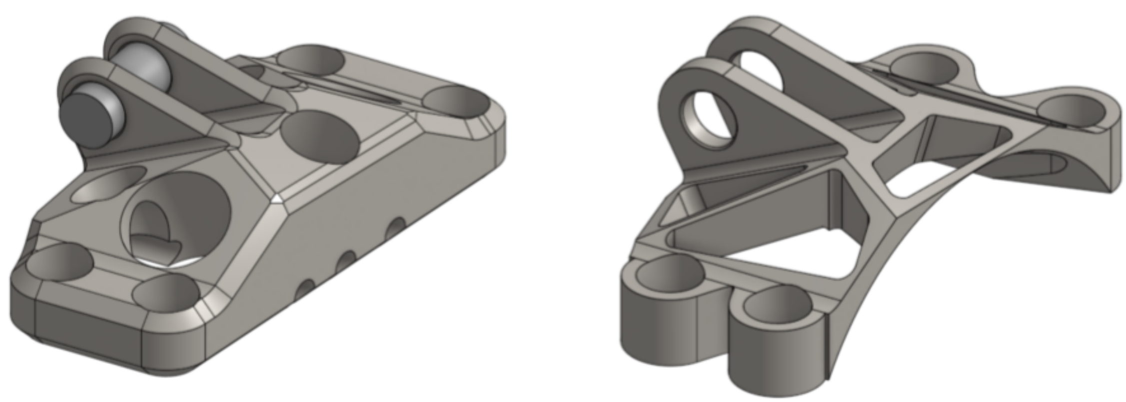


Figure 4-14. Models with thin features excluded from simulation of ultrasonic wave propagation and calculation of $a_{90/95}$

In order to simulate a realistic pulse-echo ultrasonic inspection, Gaussian noise was added with a signal to noise (SNR) ratio of 10 [78][108] using MATLAB R2018b. One hundred iterations of noise addition were conducted per simulation to calculate PoD. The peak amplitude in the reflection off the defect was recorded for each simulation to calculate $a_{90/95}$ using software mh1823-POD [78,79,109]. More information on the equations used to calculate $a_{90/95}$ can be found in [109].

Significant outliers were observed in the experimental and control groups. Any component with an $a_{90/95}$ large enough that such defects would be visible from the surface of the part was removed before statistical analysis. The number of parts fitting this criterion was evenly split amongst the experimental and control groups, with five designs from each group being removed. This left four designs in the control group and four designs in the experimental group, a much smaller sample size than originally anticipated. A t-test for equality of means showed no significant difference in the average $a_{90/95}$. The average $a_{90/95}$ for the control group was 1.95 millimeters and the average for the experimental group was 3.52 millimeters. A Cohen's d with a Hedges g correction [105] to account for small sample sizes was calculated to be >.999, indicating a large effect size. However, it is difficult to rectify the inspectability results of Chapter 3 with those observed here. The large effect sizes seem to suggest opposing results. This can be common in human subjects research, where confounding factors and variability between subjects can lead to results that are difficult to interpret. In such cases, the most direct solution is to increase sampling and apply changes to the experimental design to remove as many confounding factors as possible, discussed further in Chapter 6.

4.5 Chapter Summary

A controlled study was conducted to determine if design outcomes were changed considerably by the addition of DfI considerations. A total of twenty participants were recruited from The Pennsylvania State University with similar ages, experience with CAD, and experience with AM. Participants were randomly sorted into two even groups, with the experimental group being provided a DfI Worksheet. Participants in each group participated in two design tasks. During the second task, participants in both groups had to redesign a component to reduce its mass while ensuring it met all stated requirements and did not fail under mechanical loading. Participants in the experimental group had an additional constraint, that their parts must be inspectable using PEU.

There was no significant difference in the mass reduction of components developed by designers exposed to DfI considerations and designers in the control group. Further, the low effect size suggests that introducing DfI considerations had minimal effect on how much mass designers removed during the redesign task, independent of sample size. The trend observed in Chapter 3, that designers exposed to DfI considerations were more conservative in their material removal, could not be confirmed in this test.

There was no significant difference in peak stress of components developed by designers exposed to DfI considerations and designers in the control group. Testing the peak stress in each load condition, there was no significant difference between the experimental and control groups in any of the conditions. The low effect sizes seen in each suggest that introducing DfI considerations had minimal effect on the strength of designs, independent of sample size. The trend observed in Chapter 3, that designers exposed to DfI considerations produced stronger designs, could not be confirmed in this test.

There was no significant difference in $a_{90/95}$ for components developed by designers exposed to DfI considerations and designers in the control group. The average $a_{90/95}$ was higher in the experimental group than in the control group, combined with the large effect size, suggests an opposite effect than observed from Chapter 3. This effect also calls into question the efficacy of the DfI worksheet as an intervention. Observing no significant difference in any of the tested design outcomes, it is possible that the DfI worksheet was not sufficient as an intervention to effect design activities. To test this, analysis of think-aloud and survey data collected during the test were analyzed and results are discussed in the following chapter, Chapter 5.

Chapter 5

Effect of DfI on Designer

Introducing additional design constraints, such as inspectability constraints, into the early stages of the design process is likely to affect designer behavior and strategies. Prior work has demonstrated that external factors such as design constraints, budgetary restrictions, and limitations of available tools can affect designer emotions [112]. Emotions affect how designers process information, allocate materials, and apply strategies, all of which can greatly impact design outcomes [112]. More specifically, as designers engage in complex design tasks using CAD tools or DfX tools, designers can experience surprise or frustration [113,114]. In addition, the complexity of tasks plays a critical role in decision making, as mental workload increases with task complexity [115]. Each person has a finite capacity for mental workload, and exceeding this capacity can lead to memory loss, difficulty in perception, and poor performance [116]. As a novel DfX framework was introduced to members of the experimental group, along with the addition of a new constraint, it is important to note any observed changes in emotion and mental workload, as well as changes in design strategies. In pursuit of RQ2, *what effects do DfI considerations have on designers and the design process*, a controlled study was conducted with 20 practicing designers.

Data collected during the procedure listed in Chapter 4 can be analyzed to determine what effect DfI considerations have on designers. During the redesign task, participants were asked to think-aloud and audio was recorded. During think-aloud procedures, participants are asked to verbalize their thoughts, allowing researchers to observe some cognitive processes that can otherwise go uncaptured [117–119]. Think-aloud procedures can be used to compare concepts, themes, and cognitive strategies between groups with similar tasks and workloads [120].

The Linguistic Inquiry and Word Count (LIWC) method is used in this work to identify emotional and cognitive markers [121,122] within audio transcriptions of designers' think-aloud protocol. The creators of LIWC have classified words in terms of Summary Language Variables, Linguistic Dimensions, Grammars, and Psychological Processes, and comparing words in text to these validated dictionaries allows researchers to learn important insights into writers and speakers. Using LIWC to analyze customer reviews allowed researchers to discover important product features [123]. Analysis of Kickstarter campaigns was used to discover communication strategies that contributed to fundraiser success [124]. Analysis of think-aloud protocols has been used to assess cognitive and emotional processes during tasks [121,122]. In this study, LIWC is used to measure affective processes, positive emotions, anger, frustration, and cognitive processes. This tool was selected as a method of detecting emotional language and evidence of cognitive processes in the think-aloud procedure that occurred during the redesign task.

Surveys collected after the redesign task in Chapter 4 can be used to assess mental workload. Among these is the NASA Total Load Index (NASA-TLX), an assessment used to measure mental demand, physical demand, temporal demand, frustration, effort exerted, and self-reported performance [125]. The NASA-TLX survey is commonly used in the assessment of design tools [126–128]. The NASA-TLX is easy to administer and requires no specialized equipment. When Barnawal et al. [129] explored modes of feedback to designers on how manufacturable their designs were, the NASA-TLX was used to show that 3D representations of feedback required less mental workload to utilize than written feedback alone. Like the study by Barnawal et al., this study endeavored to understand how different treatments would affect designers and design outcomes. Using the NASA-TLX survey allowed for measurement of mental workload in both the designers exposed to DfI considerations and the designers in the control group.

Methods of evaluating design sequences are also important in understanding what impact DfI considerations had on designers. Design sequences can be charted and analyzed to help better understand the tactics used to arrive at an appropriate solution [130]. Looking at design processes that occur sequentially, some have been modelled as stochastic processes [131]. When designers actions can be categorized into well-organized states, like an idea generation state or an analysis state, it is possible to represent the design process using a Markov chain [132]. However, when states are not well defined, observations of behavior can be used to discover what states designers move through in their design process [133]. For our study, we treat the redesign task as a Markov process. Training separate Hidden Markov models (HMM) for the experimental and control groups, we search for differences in the strategies used by designers during the redesign task.

5.1 Experimental Design

Data for NASA-TLX, think-aloud, and HMM of user actions were collected during the study described in Chapter 4. In this study, 20 designers were recruited from The Pennsylvania State University were recruited for participation in a controlled study.

Participants first completed a pre-study survey via Qualtrics provided in email. This survey was used to inform participants about the study, ensure inclusion criteria were met, generate an anonymous user id used for storing all collected information, and collect information such as age, gender, their experience with CAD, their experience with AM, and their experience with NDT. On page 6 of the survey, anyone who would like to continue to the design portion of the study was provided a link to a second Qualtrics survey, where they could provide an email used to schedule the design task. While less convenient for participants to fill in two surveys, directing participants to the second survey to provide an email ensured that there was no identifying information associated with pre-study survey data, in accordance with IRB protocol. Participants then scheduled a time for the virtual experiment via zoom by email correspondence through the address provided.

Participants were separated into control and experimental groups. All participants logged into the OnShape platform, using randomly generated login credentials. Upon entering the OnShape portal, participants in the experimental group were directed to the project DfI E and participants in the control group were directed to the project DfI C. As seen in Figure 5-1, each project contained multiple tabs, seen at the bottom of the browser window.

To ensure that members in the experimental group were familiar with the DfI Worksheet, they participated in a 15-minute inspection task, and participants in the control group participated in a similar, neutral 15-minute task. During the inspection task, members of both the experimental and control groups were instructed to think-aloud. During the inspection task, members of the control group used the first three tabs provided. The first tab was the model shown in Figure 5-1. The second tab was a design drawing, which participants compared to the original design and announced any and all discrepancies between the two. The third tab included instructions on how to use some key inspection tools in OnShape. During the first task, members of the experimental group used the first four tabs. The first tab was the model shown in Figure 5-1. The second tab was the DfI Worksheet. The third tab was a list of critical features in the model. The fourth tab included instructions on how to use some key inspection tools in OnShape. Recording of the participant screen and all audio began before the inspection task began.

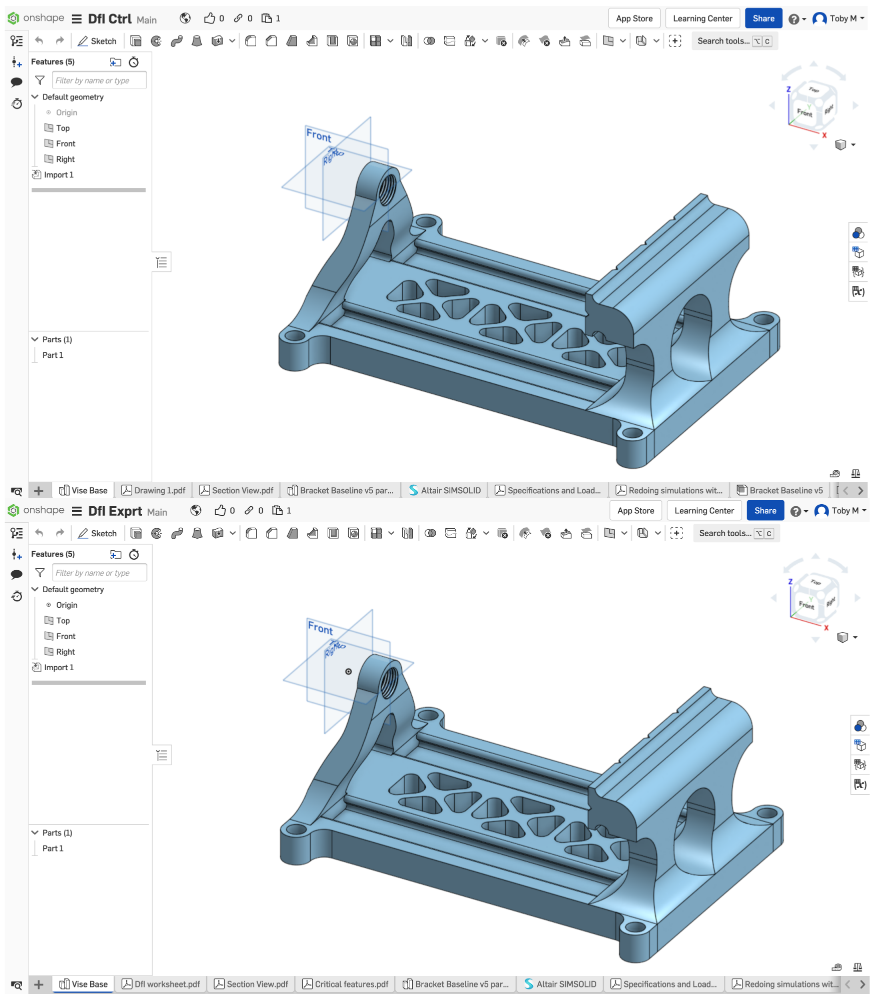
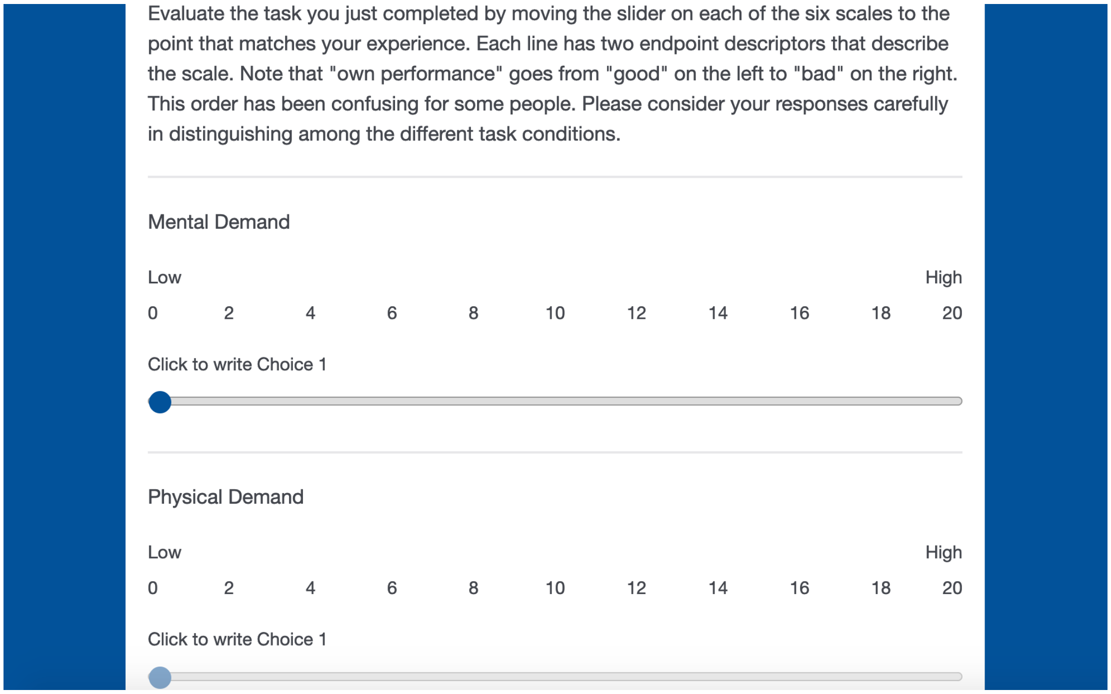


Figure 5-1. OnShape platform, showing available tabs for (TOP) Control group and (BOTTOM) Experimental group

Although the think-aloud during the inspection task would not be analyzed, Chu and Shiu [120] suggest that a warm-up is one of four practices necessary for effective think-aloud protocols. First, since many people are accustomed to thinking silently, not verbalizing their thought processes, participants need to be given time to warm-up and get used to thinking out loud. By encouraging them to think-aloud during the inspection task, participants were given this warm-up. Second, participants need to be prompted when going extended periods without verbalizing. This was a simple “please keep thinking out loud” or “just keep saying what you’re thinking”. Third, participants need to be told that all thoughts are valid, and do not need to be refined before speaking. This came in the form of verbal encouragement following the inspection task, like “What you did during that first task, saying what you were thinking, that was perfect”. Also, when participants apologized for swearing or for rambling, it was important to say, “No need to apologize, whatever you think just go ahead and say”. Finally, participants should be discouraged from conversing with the facilitator, as conversing can distract from other cognitive processes.

Following the inspection task, participants took an initial NASA-TLX survey. This survey started with one open-ended question at the top of the Qualtrics form, where participants entered their anonymous user ID. This allowed results of the TLX to be paired with the design outcomes shown in Chapter 4. After this question, participants read the instructions, shown in Figure 5-2.


Evaluate the task you just completed by moving the slider on each of the six scales to the point that matches your experience. Each line has two endpoint descriptors that describe the scale. Note that "own performance" goes from "good" on the left to "bad" on the right. This order has been confusing for some people. Please consider your responses carefully in distinguishing among the different task conditions.

Mental Demand

Low High

0 2 4 6 8 10 12 14 16 18 20

Click to write Choice 1

Physical Demand

Low High

0 2 4 6 8 10 12 14 16 18 20

Click to write Choice 1

Figure 5-2. Example of NASA-TLX form, including instructions and two of the six questions included in the full form

Participants moved sliders to report the amount of mental demand, physical demand, and temporal demand during the inspection task, as well as effort exerted, frustration experienced, and a rating of their own performance. The sliders were continuous, with a resolution of 0.5.

Following the first NASA-TLX survey, designers were given five minutes to practice using OnShape to change an imported geometry. Participants were told to modify the design provided in the inspection task using any of the tools provided in OnShape. This was important since OnShape was selected because of its function as an online CAD tool, ideal for work with Covid-19 safety protocols, but its use was not widespread at The Pennsylvania State University. Although all participants had experience with CAD, experience with OnShape was not required for participation in this task. This limitation is discussed further in Chapter 6.

After the practice session, participants were explained the task for the redesign task. Participants in the control group were told to reduce the mass of the part by at least 50% and the part must meet all specifications listed on the sheet provided in the specifications and loading conditions sheet. Participants in the control group were told to reduce the mass of the part by at least 50%, the part must meet all specifications listed on the sheet provided in the specifications and loading conditions sheet, and the part must be inspectable using PEU. Participants were also provided access to Altair Simsolid, a software where they could run FEA on the part they designed, as well as written instructions to re-run FEA on the part they designed for each of the loading conditions.

During the redesign task, members of the control group could use any of the first seven tabs provided. However, the fourth, fifth, sixth and seventh tabs were most applicable to the redesign task. The fourth tab was the model editor, where designers could make changes to the model. The fifth tab was Altair Simsolid, where designers could run FEA on the parts they had designed. The sixth tab was a document labeled Specifications and Loading conditions, which listed all requirements for the redesign task. Finally, the seventh tab included instructions on how to rerun FEA using the updated geometry.

During the redesign task, members of the experimental group could use any of the first eight tabs. However, the fifth, sixth, seventh, and eighth tabs were most applicable to the redesign task. The fifth tab was the model editor, where designers could make changes to the model. The sixth tab was Altair Simsolid, where designers could run FEA on the parts they had designed. The seventh tab was a document labeled Specifications and Loading conditions, which listed all requirements for the redesign task. Finally, the eighth tab included instructions on how to rerun FEA using the updated geometry.

During the redesign task, participants were instructed to think-aloud. If participants went for 1 minute without verbalizing their thoughts, they were prompted to continue. At the end of the redesign task, participants were asked to complete the second round of the NASA-TLX survey. This survey was identical to the first TLX survey, but participants were instructed to respond based only on the redesign task.

In pursuit of answering RQ2, data from the same controlled study in Chapter 4 was analyzed. Results of NASA-TLX filled out after the redesign task were analyzed and discussed in section 5.1. Think-aloud protocols recorded during the redesign task were transcribed and analyzed using LIWC software, as described in section 5.2. Transcription of user actions during the redesign task was performed using Solomon coder, and HMM were trained using MATLAB, discussed in section 5.3.

5.2 NASA TLX Results

Analysis of NASA-TLX occurred for mental demand, physical demand, temporal demand, performance, effort, and frustration. The Shapiro-Wilk test for normality showed responses in physical demand and temporal demand did not match a normal distribution. In addition, outliers were seen in the categories physical demand, temporal demand, and frustration. The Mann-Whitney U test is a non-parametric test recommended for comparing two groups with outliers [134].

Mann-Whitney U tests were run to determine if there were differences between the control and experimental groups in any of the fields tested by the NASA-TLX survey. As shown in Table 5-1, there were no significant differences in the experimental and control groups for Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, or Frustration. This suggests that the addition of DfI considerations did not significantly increase the mental workload experienced by designers during the redesign task. This is important to note, as a significant increase in mental workload could significantly hinder decision-making processes [116]. However, considering the small sample size, continued collection of data with the NASA-TLX will be important for early detection of trends toward increased mental workload, as described in chapter 6.

Table 5-1. Results of Mann-Whitney U comparing NASA-TLX results for control and experimental groups

TLX Category	Control		Experimental		U	z	p	Cohen's d
	Median	Mean	Median	Mean				
Mental Demand	14	13.5	15	14.3	54.5	.343	.739	0.153
Physical Demand	1.5	3.8	3	3.7	60.5	.805	.436	0.361
Temporal Demand	12.5	12.2	14.0	13.1	57.0	.532	.631	0.238
Performance	7	7.3	7	7.3	49.0	-.076	.971	0.034
Effort	14	13.7	15	14	54.5	.343	.739	0.153
Frustration	5	6.1	7.5	8.3	58.0	.609	.579	0.273

5.3 LIWC Results

Transcripts of participant speech during redesign were used to expound upon results seen in the NASA-TLX. Categories classified by LIWC were selected which demonstrate mental demand, including cognitive processes, insight, and recognition of cause. In addition, categories were selected that demonstrate frustration, including affect, negative emotions, anger, anxiety, and swear/explicit language.

Mann-Whitney U tests were run to determine if there were differences between the control and experimental groups in language indicative of cognitive processes. The LIWC 2015 software finds evidence of cognitive processes in text by searching for words in the LIWC dictionary defined for six sub-categories. Looking for evidence of cognitive processes was important in answering RQ2, finding evidence that designers who were given DfI considerations showed different patterns of thinking than those who had not. These sub-categories include insight, causation, discrepancy, tentative, certainty, and differentiation. Words included in the LIWC dictionary for insight include "think" and "know". When participants say words from the insight subcategory, it shows they have gathered insight from something being observed. For example, participants said during the redesign task "I think I took too much out" and "I think that's actually creeping into the danger zone".

Words for causation include "because" and "effect". When participants say words from the insight subcategory, it shows they have recognized a cause. For example, participants said during the redesign task "Because if that is the case, probably it makes sense for me to be adding those fillets" and "just because I don't see a lot of stress concentration in that section".

Words for discrepancy include "should" and "would". This shows that participants have recognized a discrepancy between what they saw in the design task and what they expected. For example, participants said, "it should be already equal" and "I would've put points down and then done".

Words included in the LIWC dictionary for tentative include “maybe” and “perhaps”. When analyzing text, finding words in the tentative subcategory show the speaker was uncertain or not confident in their choice. Participants sometimes used this language during the redesign task, saying things like “Maybe we'll change some material out of there” and “Maybe I can just turn it like this direction”.

Words for certainty include “always” and “never”. Counter to words in the tentative category, words for certainty show that a speaker knows something absolutely, that they are sure of what they know. Some examples include “I never checked if it was symmetric” and “We can always delete it later”.

Words for differentiation include “hasn’t” and “else”. When speakers use language in the differentiation subcategory, they show that they have made a distinction between disparate things. Participants said things like “I don't know what else I could take out” and “nothing else needs to be parallel”.

Table 5-2. Results of Mann-Whitney U comparing LIWC analysis results of cognitive processes, insight, and recognition of cause for control and experimental

LIWC Category	Control		Experimental		U	z	p	Cohen ’s d
	Median	Mean	Median	Mean				
Cognitive Processes	13.81	14.27	13.13	12.77	17.0	-2.044	.043	1.074
Insight	2.09	2.08	1.84	1.92	27.0	-1.156	.274	0.485
Causation	2.29	2.34	2.23	2.18	32.0	-.711	.515	0.332
Discrepancy	2.64	2.63	2.74	2.62	43.0	.267	.829	0.014
Tentative	4.52	4.24	3.96	3.95	31.0	-.800	.460	0.334
Certainty	1.34	1.35	.96	.94	21.0	-1.69	.101	1.079
Differentiation	3.63	3.70	2.82	3.70	26.5	-1.20	.237	0.609

As shown in Table 5-2, there were significant differences in the experimental and control groups for language indicative of cognitive processes. The median and mean cognitive processes were higher in the control group. However, there were no significant differences seen in the six sub-categories, suggesting small differences in the subcategories added up to one significant difference. This suggests that introducing DfI consideration did change some of the thought processes of designers.

Looking at the effect sizes, we see that there is a large effect size in the sub-category “certainty”. The median and mean values for certainty were higher in the control group than in the experimental group. This shows that during the redesign task, participants in the experimental group were less sure, that the addition of new considerations in the design process may have added doubts. This is to be continually monitored as work on DfI continues, expanded on in Chapter 6.

Mann-Whitney U tests were run to determine if there were differences between the control and experimental groups in affect. Affect is a measure of emotional content made up of 2 sub-categories, which are positive emotions and negative emotions. Negative emotions is broken further into anxiety, anger, and fear. Words for positive emotions include words like “nice” and “sweet”. When a speaker uses words in the positive emotions subcategory, it suggests they are in a positive mind frame or they are experiencing positive emotions. Participants said phrases like “It got to orient me nice, okay, awesome” and “Nice, okay, so I'll just need to do that for...”.

Words for negative emotions include words like “hurt”, “ugly”, or “nasty”. When a speaker uses words in the negative emotions subcategory, it suggests they are in a positive mind frame, or they are experiencing negative emotions like anxiety, anger, and fear. Participants made statements like “I hate that it keeps working its way over there” and “right now, we're at 103 at worst”.

As shown in Table 5-3, there were no significant differences in the affect found in experimental and control groups. However, there was a medium effect size observed in negative emotions and anger. The mean and median values for negative emotions and anger were higher in the control group than the experimental group. This runs counter to what is expected, that the addition of new considerations should increase frustration. As prior work has demonstrated that additional constraints and harder tasks can increase feeling of frustration [135]. It is possible that a broad, open-ended design task like the one provided to the control group may be frustrating to complete, and the addition of a constraint made the design process clearer. It is also possible that this result will not be significant at larger sample sizes. The affective processes of designers should continue to be monitored as work on DfI continues, discussed further in Chapter 6.

Table 5-3. Results of Mann-Whitney U comparing LIWC analysis results of affect, negative emotions, anxiety, anger, and sadness for control and experimental groups

LIWC Category	Control		Experimental		U	z	p	Cohen's d
	Median	Mean	Median	Mean				
Affect	5.9	5.66	6.34	6.44	53.0	1.155	.274	.102
Positive emotions	4.46	4.39	5.28	5.11	55.0	1.333	.203	.170
Negative emotions	1.205	1.179	1.125	1.12	33.0	-.622	.573	.600
Anxiety	.405	.441	.410	.369	39.0	-.089	.965	.378
Anger	.090	.145	.075	.048	35.0	-.445	.696	.524
Sadness	.130	.158	.120	.161	38.0	-.178	.897	.414

5.4 Analysis of Participant Actions

Transcription of user actions was performed using Solomon Coder beta 19.08.02. Solomon Coder is a free-to-use software used for behavioral coding. It allows you to create your own codes for specific actions, then assign those codes to frames in video. Transcription began when the forty-five-minute timer started and concluded when participants were told their time had expired. Participants' actions were coded into one of nine codes: Review Design, Review Specifications and Loading Conditions, Review Simulation, Review DfI Worksheet, Edit Sketch, Add/Remove Material, Review Instructions, Review DfI Worksheet, Edit/Run Simulation, and Off OnShape.

Review Design was assigned whenever participants had the model editor open, but no sketch or extrude tools were open, as shown in Figure 5-3. During this stage, participants oriented the part and inspected the geometry.

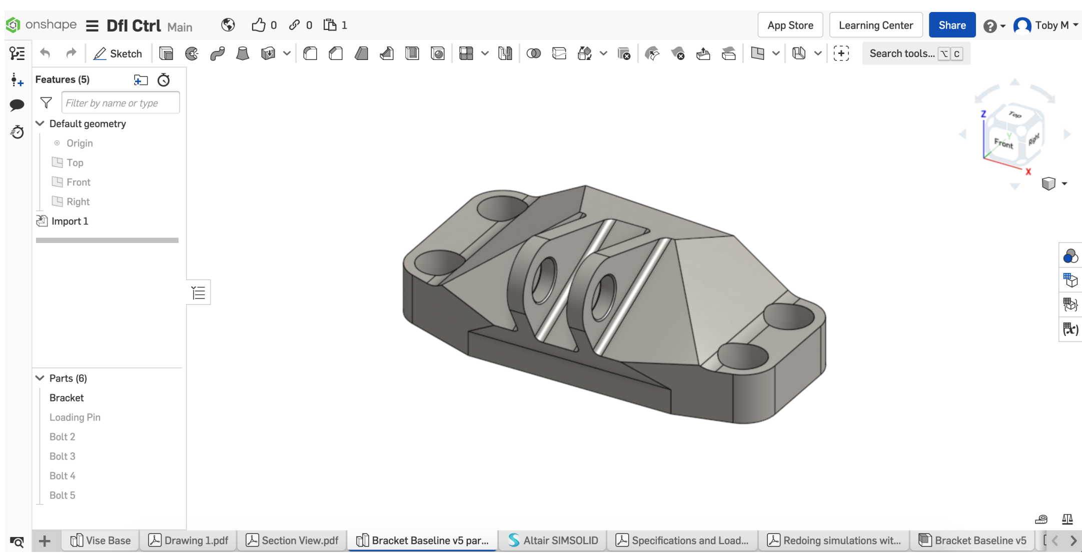


Figure 5-3. Example of on-screen display coded as 'Review Design'

Edit Sketch was coded anytime the model editor was open with sketch tools shown, as shown in Figure 5-4. While sketch entities do not directly change the 3D geometry, they are the building blocks for any sketch-based modelling techniques. Using sketches, designers can define a near-infinite number of complex geometries which can then be used to perform simple Boolean operations or more complex operations available through the modelling software.

Add/Remove Material was coded anytime the model editor was open with a tool selected used for adding or removing material, as shown in Figure 5-5. During this phase, participants can commit changes to the 3D geometry. While review design and edit sketch were important steps in the design process, this step is the most directly observable through design outcomes. As such, coding for these actions were crucial in understanding how designers reached design outcomes.

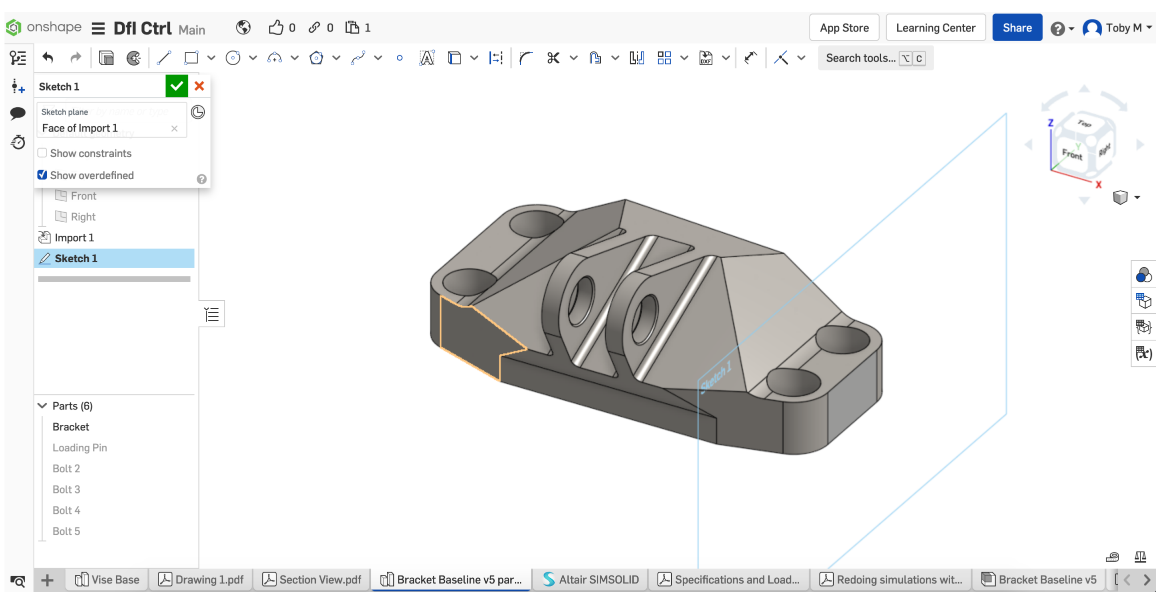


Figure 5-4. Example of on-screen display coded as 'Edit Sketch'

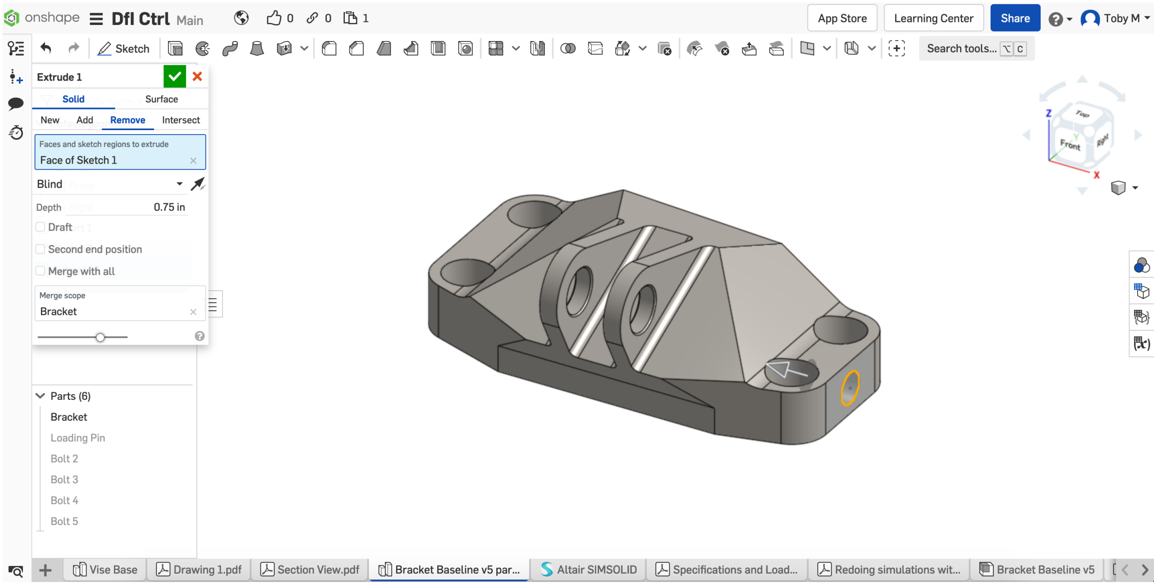


Figure 5-5. Example of on-screen display coded as 'Add/Remove Material'

Review Specifications and Loading conditions was assigned whenever participants had the specifications and loading conditions open, as shown in Figure 5-6. This was the only way that participants were able to read design constraints as listed, including information about manufacturing, loading conditions, and the failure condition.

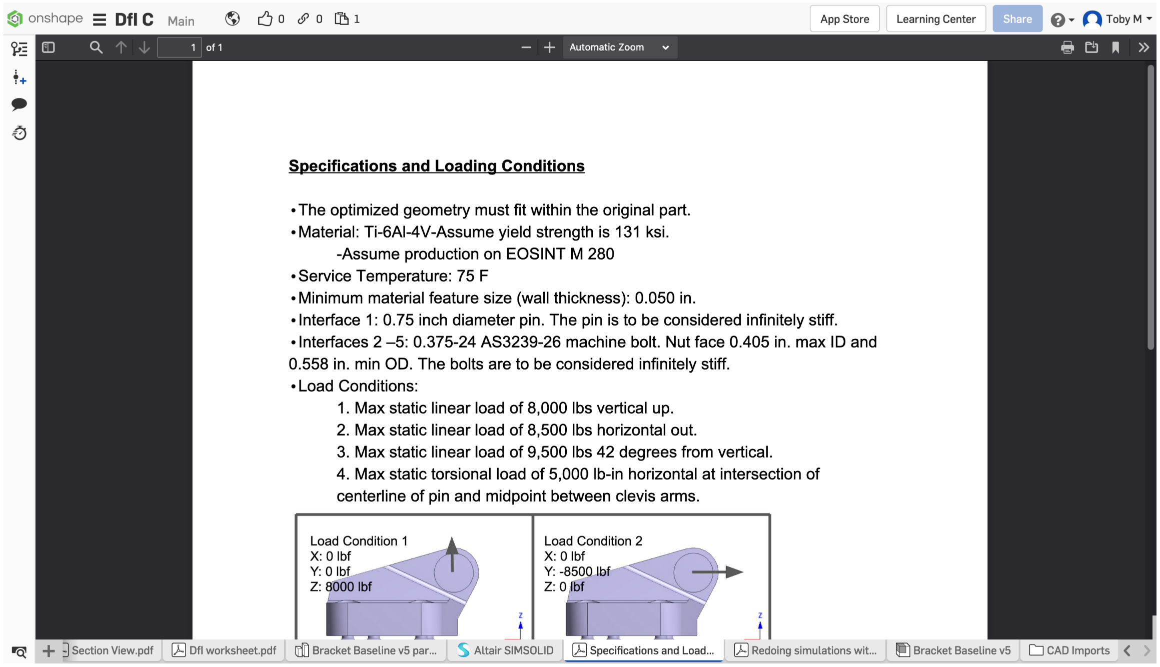


Figure 5-6. Example of on-screen display coded as ‘Review specifications and Loading Conditions’

Review Simulation was assigned whenever Altair Simsolid was open and all simulations were complete, as shown in Figure 5-7. When reviewing simulations, designers were able to check the maximum stress and see the distribution of stress along the part. This information can be valuable in deciding where to cut material to reduce weight or add material to reduce stress risers.

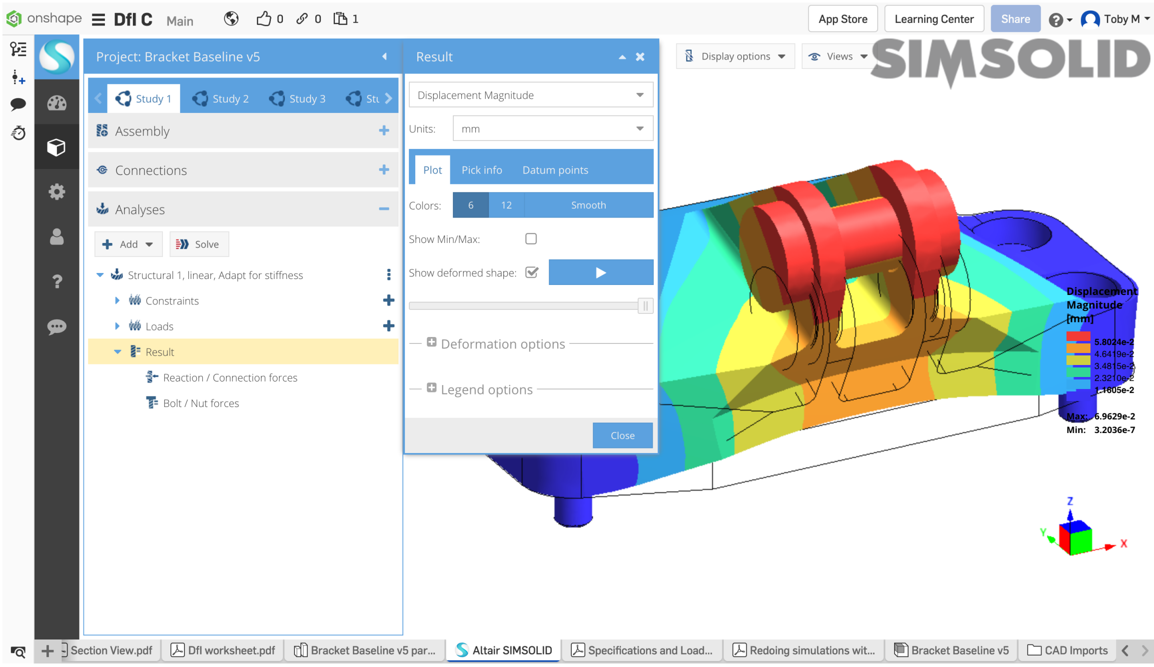


Figure 5-7. Example of on-screen display coded as 'Review Simulation'

In comparison, Edit/Run Simulation was assigned whenever Altair Simsolid was open and either geometry or loading conditions were changed, such that a solution was not available for one or more loading conditions, shown in Figure 5-8. This allowed designers to check their designs had not exceeded the failure conditions, and to see where stress was distributed across the part.

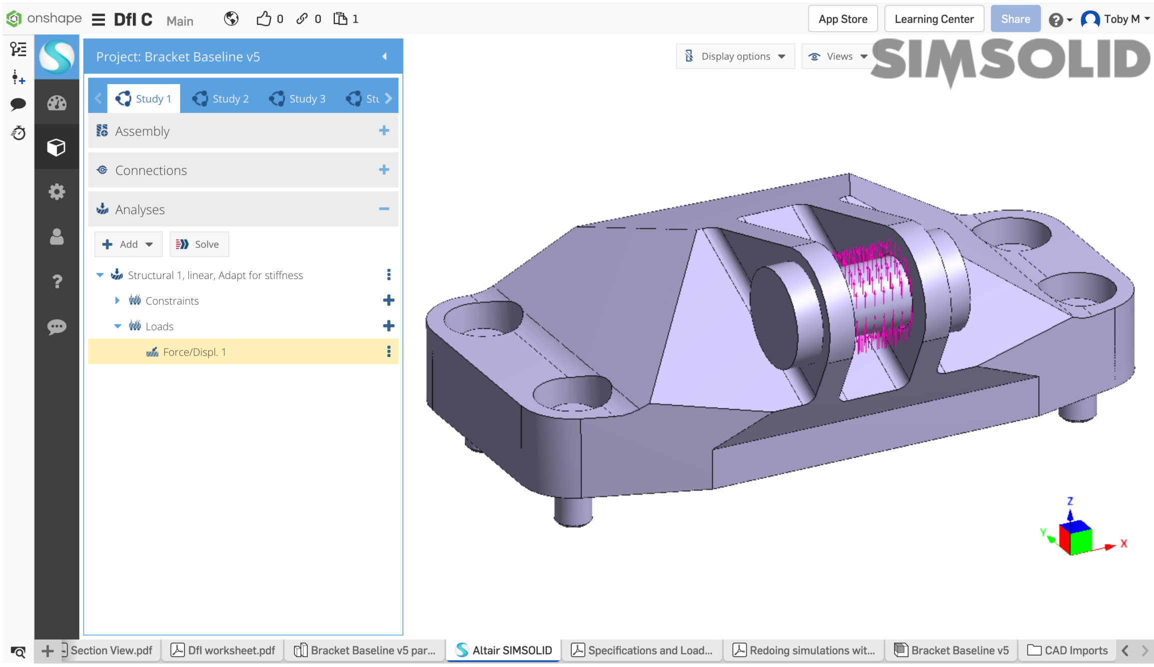


Figure 5-8. Example of on-screen display coded as 'Edit/Run Simulation'

Review instructions, shown in Figure 5-9, was coded anytime participants referred to additional material provided, including instructions on using the section view or redoing simulations with updated geometries. While the OnShape program worked nicely with social-distancing protocols, it is not the primary modelling software taught at Penn State or used by most designers. Noting the time spent searching for information on important features is important to consider, as it likely played a role in determining the design outcomes.

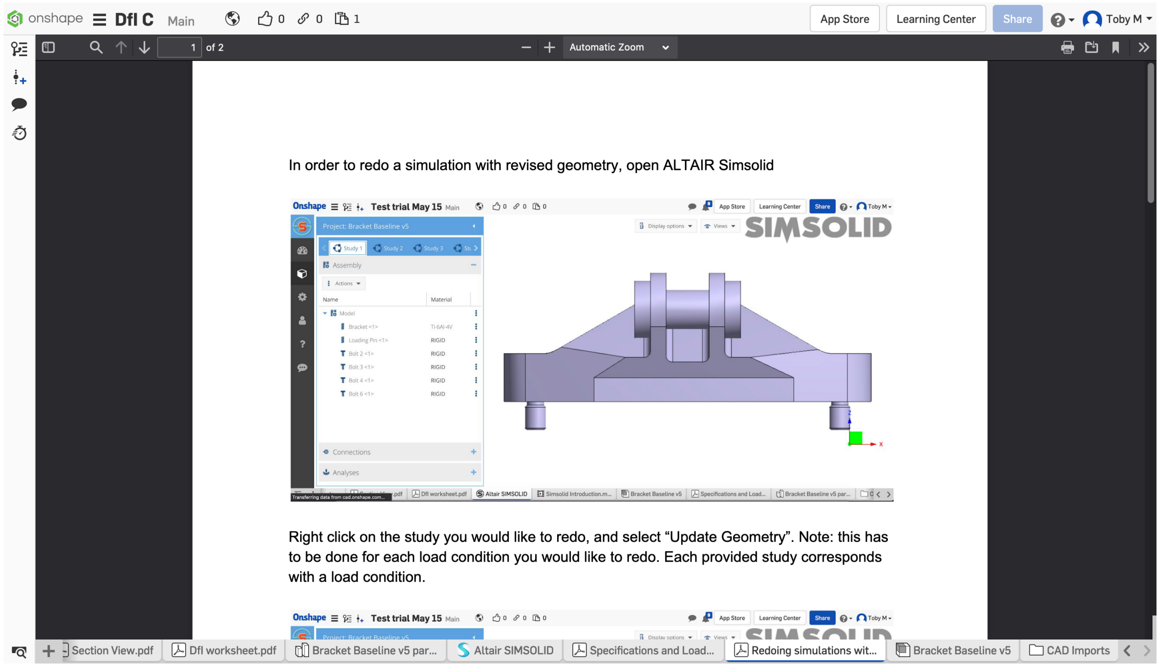


Figure 5-9. Example of on-screen display coded as ‘Review Instructions’

Review DfI Worksheet was a code unique to the experimental group. While similar to review instructions, this code is unique to the intervention applied. If participants referred to the worksheet to understand how the surface or internal geometry of their design would impact inspectability, or if they assessed their part using the worksheet before applying further changes, it would be very important to note.

Finally, anytime the participant left OnShape for any reason, it was coded as Off OnShape. Some participants instinctively went to search engines for things like unit conversion or looking up technical specifications of materials. At such times, the facilitator guided them back to the task and answered any questions before encouraging them to continue with the redesign. For completeness of the list of user actions, Off OnShape was included as a code.

It is important to note that one participant experienced technical issues, resulting in a loss of connection twice during the protocol. During these losses of connection, the participant was unable to make further changes until their connection to OnShape was re-established, and the timer was paused until connection was restored.

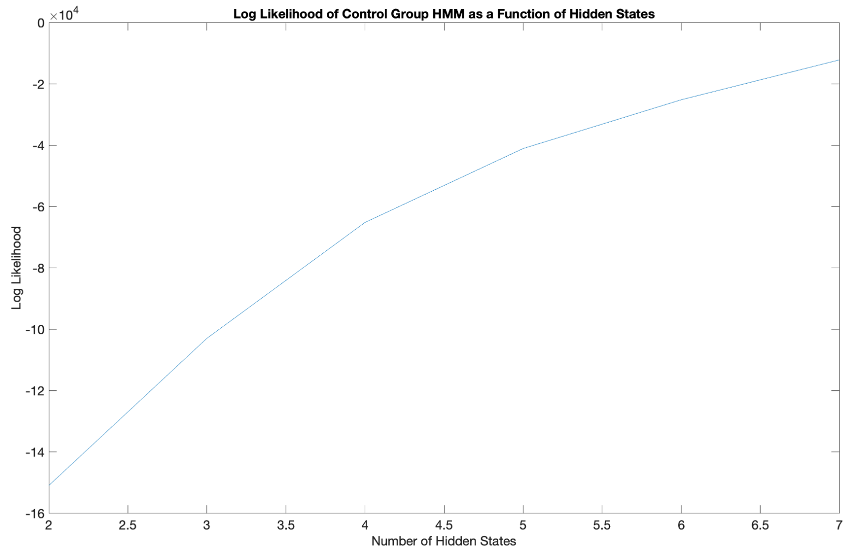
Before training HMM, analysis was run to see if designers in the experimental groups spent significantly more time performing any of these actions than the control group. While less complex than the HMM, one group spending significantly more time reviewing instructions may signify a difference in the levels of experience with CAD, or more cognitive load leading to poor performance in the redesign task. Mann-Whitney U tests were run to determine if there were differences between the control and experimental groups in any of the coded actions, as shown in Table 5-4.

Table 5-4. Results of Mann-Whitney U comparing time spent performing each coded action for control and experimental groups

Action	Control		Experimental		U	z	p
	Median	Mean	Median	Mean			
Review Design	663.5	648.9	684.3	710.3	55.5	.416	.684
Review Specifications and Loading Conditions	157.3	171.0	158.7	157.5	48.5	-.113	.912
Review Simulation	469.1	449.1	501.1	490.5	57.5	.567	.579
Review Instructions	75.6	98.7	100.7	109.4	54.5	.340	.739
Edit Sketch	851.3	737.9	593.0	550.6	33.5	-1.248	.218
Add/Remove Material	284.0	291.6	370.4	373.6	70.5	1.55	.123
Edit/Run Simulation	235.9	229.8	190.9	271.8	45.5	-.340	.739
Off OnShape	0.4	23.2	0.0	7.4	36.5	-1.15	.315

It is important to note that, for the purposes of comparing the control and experimental groups directly, 'Review Instructions' and 'Review DfI Worksheet' were combined into one category. No significant differences between the experimental and control groups were noted in the time spent in any of the coded actions.

Training of HMM occurred in MATLAB R2018a (9.4.0.813654) following the procedure listed in [136]. The Baum-Welch algorithm was used to train separate HMM for the control and experimental groups. To begin training, the number of hidden states *k* was assigned to two, the minimum number of states. To ensure the repeatability of results, each model was trained five times, the log-likelihood was measured for each iteration, with the highest log-likelihood recorded before *k* increased by one. The process repeated until the experimental and control group models were trained for up to seven hidden states. The number of hidden states *k* selected was the lowest possible value of *k* had a log-likelihood that was not significantly different than that of the highest value of *k*. As shown in Figure 5-10, the value of *k* was six for both the control and experimental groups.



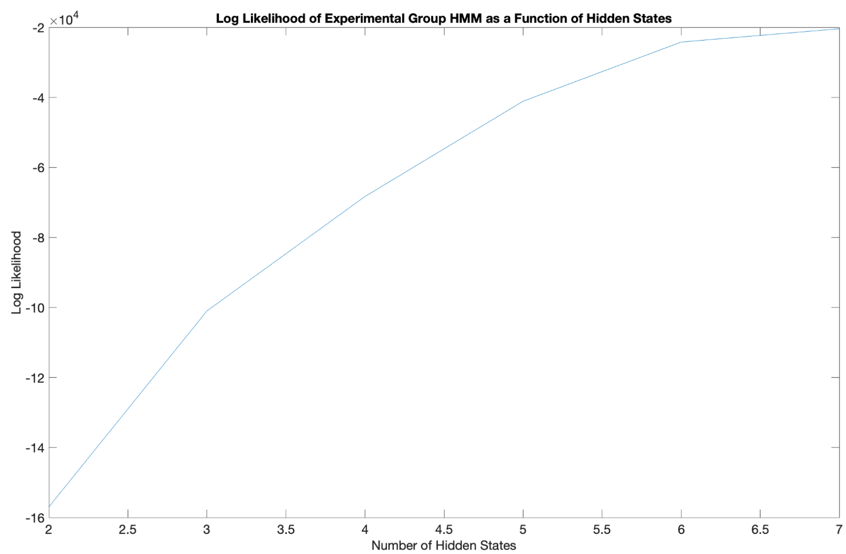


Figure 5-10. Log likelihood plotted as a function of the number of hidden states (*k*) for (TOP) control group and (BOTTOM) experimental group

The transition and emission matrices for the control group are shown in Figure 5-11. The strong diagonal seen in the transmission matrix means that if designers were in a particular state, they would have a high probability of transferring back into that state. This is likely due to the high resolution used for coding combined with the tendency of participants to stick with the same action. Five of six states were made up almost entirely of one action, suggesting the actions are distinct. The remaining state has high emission probabilities for ‘Review Instructions’ and ‘Edit/Run Simulation’. It is likely that in this state, participants are referring to the tab ‘Redoing Simulations with Updated Geometry’ before returning to rerun FEA. This suggests many of participants in the control group were either unfamiliar with Altair Simsolid or preferred to use the written instructions.

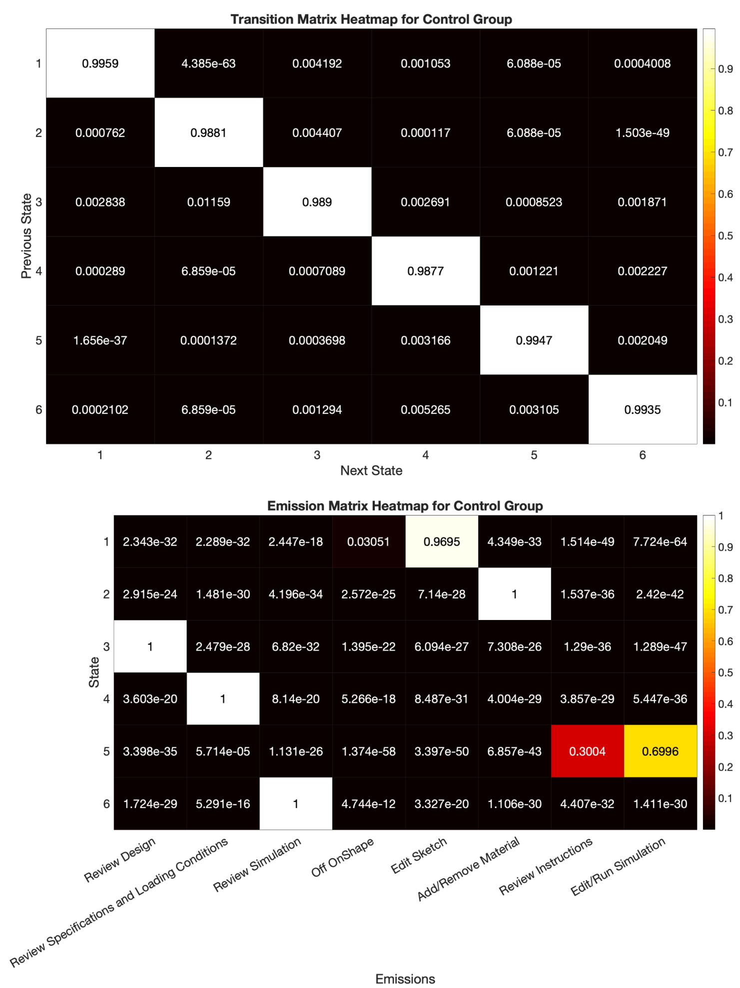
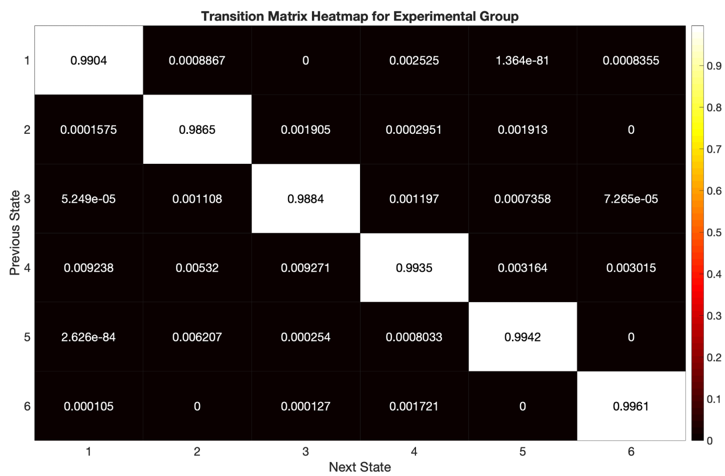


Figure 5-11. For HMM trained with actions from Control Group (TOP) Transition Matrix and (BOTTOM) Emission Matrix

The transition and emission matrices for the experimental group are shown in Figures 5-12. The strong diagonal seen in the transmission matrix means that if designers were in a particular state, they would have a high probability of transferring back into that state. Five of six states were made up almost entirely of one action, suggesting the actions are distinct. The remaining state has high emission probabilities for 'Review Design' and 'Review Simulation'. Neither of these actions is used to directly make changes to the part



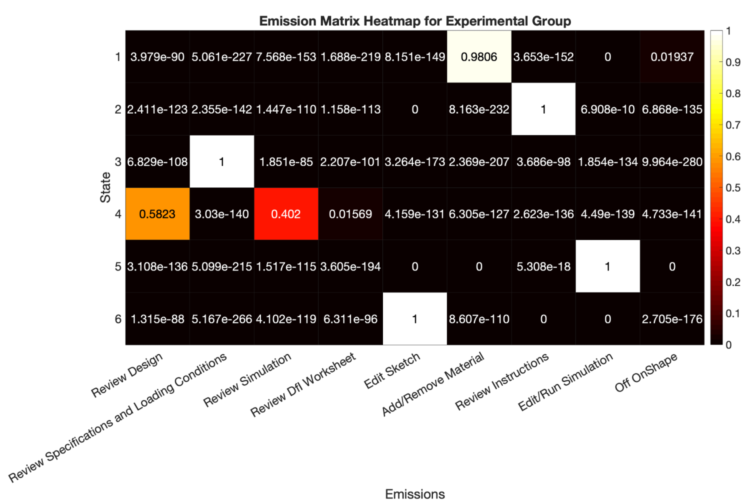


Figure 5-12. For HMM trained with actions from Experimental Group (TOP) Transition Matrix and (BOTTOM) Emission Matrix

but are used for gathering information. This may be related to the significant difference in cognitive processes, that this was the observable change in design process that followed that change. It may also be related to the high effect size of certainty, where participants in the experimental group demonstrated less certainty. These factors may have led to the emergence of a searching/planning state.

While the transmission matrices for the control and experimental groups appear similar, unique states observed in the emissions matrices show differences in the strategies used by designers exposed to DfI considerations. In the control group, five of the six states had high emissions probabilities of one and only one action. The sixth state had high emissions probabilities in ‘Review Instructions’ and ‘Edit/Run Simulation’. In this state, designers are likely referring to the provided ‘Redoing simulations with updated geometry’ sheet to run FEA and determine the strength of their designs. However, the same state is not observed in the experimental group. In the experimental group, five of the six states had high emissions probabilities of one and only one action. The sixth state had high emissions probabilities in the actions ‘Review Design’ and ‘Review Simulation’. In this state, designers are likely searching for information or planning the next step. This may be a change in design process related to the decrease in cognitive processes seen in designers exposed to DfI considerations. It may also be related to the high effect size seen with certainty. Designers exposed to DfI considerations may have been less certain of their design decisions, leading to the emergence of a searching state. Based on these results, it is likely that the introduction of DfI considerations affected designers and design processes.

5.5 Chapter Summary

A controlled design study was performed to determine if and how designers were effected by the introduction of DfI considerations. A total of 20 designers participated in 2 design activities, an inspection task and a redesign task. Half the designers were randomly assigned to the experimental group, a group who received and used the DfI Worksheet during the inspection task. The other half did not receive any instruction on DfI considerations but participated in a neutral task. All participants engaged in think-aloud protocols during the inspection task, followed by a NASA-TLX survey and five minutes of practice with OnShape design tools.

Following five minutes of practice with OnShape, all designers participated in a similar redesign task. Members of the control group were provided a digital model and were required to reduce the weight by half while meeting all listed constraints and ensuring the part would not fail under four given loading conditions. Members of the experimental group were provided a digital model and were required to reduce the weight by half while meeting all listed constraints, ensuring the part would not fail under four given loading conditions, and ensuring the part was inspectable using PEU. During the redesign task, participants verbalized their thoughts, as per the think-aloud protocols. The participants' screen was recorded during the redesign task to capture their design process.

Analysis of NASA-TLX showed no significant difference in the mental workload of those designers exposed to DfI considerations as compared to the control group. This was counter to the hypothesis that the introduction of one more, unfamiliar constraint would lead to a higher mental workload. Mental workload typically increases with the number and difficulty of tasks , until mental capacity is reached [116]. It is possible that the redesign task was difficult enough that it brought even members of the control group to their mental capacity. One possibility for future studies is to give a validated task of known difficulty before the redesign task, to get a baseline for mental workload measured by NASA-TLX [137].

Analysis using LIWC showed significant differences in the cognitive processes of those exposed to DfI considerations as compared to those not exposed. This suggests the addition of new information or new constraints may have limited some cognitive functions. This is in line with literature that states that mental capacity is limited, and that workload beyond that capacity may negatively impact cognitive processes. We hypothesize that the additional inspectability constraints may have induced a higher workload, however this should be investigated further as NASA TLX results suggest no significant difference in mental workload between groups. some cognitive processes [116].The effect sizes of cognitive processes, certainty in particular, suggest that designers may have been less certain of their choices after using the DfI worksheet. This was expected, as the introduction of new considerations was likely to require time to process information. Further, medium effect sizes in affective processes, particularly anger, suggest that designers exposed to DfI considerations may have experienced less anger during the redesign task. This runs counter to the expected result, as the addition of a, unfamiliar and difficult constraint could have increased feelings of frustration [135]. However, differences in problem framing could have contributed to this trend. The addition of the inspectability constraints in this largely open-ended design task may have made the task feel less ambiguous and lessened designers feeling of negative emotions. This trend may or may not become significant as continued study increases sample sizes.

Continued monitoring of negative emotions may be beneficial in further refining DfI considerations. [135]. However, differences in problem framing could have contributed to this trend. The addition of the inspectability constraints in this largely open-ended design task may have made the task feel less ambiguous and lessened designers feeling of negative emotions. This trend may or may not become significant as continued study increases sample sizes. Continued monitoring of negative emotions may be beneneficial in further refining DfI considerations.

Finally, the results of HMM showed some difference in the designer strategies of designers exposed to DfI as compared to those who were not. While the transmission matrices for the control and experimental groups appear similar, unique states observed in the emissions matrices show differences in the strategies used by designers exposed to DfI considerations. In the control group, five of the six states had high emissions probabilities of one and only one action. The one remaining state, the fifth state had high emissions probabilities in 'Review Instructions' and 'Edit/Run Simulation'. In this state, designers are likely referring to the provided 'Redoing simulations with updated geometry' sheet to run FEA and determine the strength of their designs. However, the same state is not observed in the experimental group. In the experimental group, five of the six states had high emissions probabilities of one and only one action. The one remaining state, the fourth state, had high emissions probabilities in the actions 'Review Design' and 'Review Simulation'. Based on these results, it is likely that the introduction of DfI considerations affected designers and design processes.

Chapter 6

Discussion and Implications for Field

Using AM, designers can design components with far more complexity than was ever possible with traditional manufacturing approaches. Components with such complexity pose unique challenges for inspection using existing QA/QC techniques and mature NDE technologies. To ensure that components can be accurately and efficiently characterized using existing technologies, designers must keep quality in mind early in the design process. The current work sought to propose a novel DfX framework and created considerations for inspection with NDE.

To determine if a DfI framework was appropriate for recommendation for use in industry, two research questions needed to be answered,

3) *What effects do DfI considerations have on design outcomes, including inspectability*?
4) *What effects do DfI considerations have on designers and the design process?*

A DfI framework will need to help designers easily and consistently design parts which are easily inspected using mature NDE technologies. However, introducing DfI considerations should not significantly interfere with design practices or negatively impact designers.

6.1 Summary of Results

In answering RQ1, there appeared to be little effect on design outcomes when introducing DfI considerations. Looking at Chapter 4, there was no significant difference in the change in volume, in the peak stress in any of the loading conditions, nor in the inspectability. However, a large effect size does suggest that the designers exposed to DfI worksheet may have produced components that were less inspectable. Seeing the conflicting messages from the high effect size in Chapter 3 and the lack of significance, it is difficult to say if there was any impact on inspectability. If there was, the effect may be inconsistent.

In answering RQ2, there may be some effect of DfI considerations on designers and design processes. In chapter 5, there was no significant difference between the control and experimental groups in mental demand, physical demand, temporal demand, frustration, effort, or self-reported performance. Although there were no significant differences in affective processes, there was a significant difference in the cognitive processes as measured by LIWC. Designers using the DfI worksheet had lower scores for cognitive processes, suggesting the introduction of DfI considerations negatively impacted designer thought processes. The large effect size seen in certainty suggests that participants may not have been as assured in their design decisions after being exposed to DfI considerations. However, the large effect size in anger suggests that participants exposed to DfI considerations may have felt less frustration during the redesign task. This difference may be due to the difference in problem framing, where the addition of the inspectability constraint made the task feel less ambiguous. Finally, HMM showed some changes in design strategies. Both experimental and control groups appear to have six hidden states, and five of those six states have very high emissions probability in one and only one coded action. The remaining state, the fifth state, had high emissions probabilities in 'Review Instructions' and 'Edit/Run Simulation'. In this state, designers are likely referring to the provided 'Redoing simulations with updated geometry' sheet to run FEA and determine the strength of their designs. In contrast, the sixth state had high emissions probabilities in the actions 'Review Design' and 'Review Simulation'. In this state, designers are likely searching for information or planning the next step. This may be a change in design process related to the decrease in cognitive processes seen in designers exposed to DfI considerations, or a change related to the high effect size of certainty. The results seen in chapter 5 suggest that introducing DfI considerations can affect designers and design processes.

- Chapter 2: Literature review was used to identify major and minor factors to inspectability using ultrasonic testing. In total, there were five major factors identified, including material, geometry, operator, machine, and environment. These five major factors were composed of eighteen minor factors. Two of the major factors, material and geometry, were identified as highly affected by early design choices, and were the focus of heuristic development. In total, six heuristics were created.

  1. Increase the radius of curvature for a rounded or sharp surface surrounding an important feature

  2. Reduce the number of thin, plate-like features

  3. Important features should be placed near the part surface or at a point in line with the transducer

  4. Remove a material interface that is between the part surface and an important feature

  5. Remove a mechanical (mating) interface

  6. Add a port to an internal cavity through which liquid can be introduced

- Chapter 3: A design tool referred to as the DfI Worksheet was created using these heuristics. Following three major revisions, the DfI worksheet was used in an initial test to determine what effect DfI considerations had on design outcomes. With a small population size, there was no significant difference between designers exposed to the in the mass, maximum stress, or inspectability of components. However, the large effect size suggested that designers exposed to DfI considerations may be more conservative with material removal and may produce components which are more inspectable.
- Chapter 4: Following significant revision to the design study, a larger group of designers participated in redesigning an engine bracket. Despite the larger sample size, there was not a significant difference between designers who were exposed to DfI considerations and designers who had not in terms of the amount of material they removed, the maximum stress during mechanical loading, or the inspectability. A large effect size suggests that, in this case, designers exposed to DfI considerations may have created designs which are less inspectable. The effect sizes seen in Chapter 3 appear to be in conflict with the effect sizes found in Chapter 4, but this may be due to confounding factors or the small sample sizes. Due to the lack of significant results, it is not possible to assume there was any significant impact to design outcomes that came about when designers were introduced to DfI considerations.
- Chapter 5: Introduction of DfI considerations likely effected designers and design outcomes. When analyzing the think-alouds and NASA-TLX, there was no significant change in mental workload. However, there was a significant

difference in the cognitive processes, with designers exposed to DfI considerations showing less evidence of cognitive processes. High effect sizes in terms of certainty and anger suggest that participants exposed to DfI considerations may have been less sure of their choices but may have experienced less anger. However, a larger sample size is needed to determine if this result is significant. After using user actions to train HMM, unique states emerged for the control and experimental groups. For member of the control group, the sixth state had high emissions probabilities in 'Review Instructions' and 'Edit/Run Simulation'. In this state, designers are likely referring to the provided 'Redoing simulations with updated geometry' sheet to run FEA and determine the strength of their designs. In contrast, the sixth state had high emissions probabilities in the actions 'Review Design' and 'Review Simulation'. In this state, designers are likely searching for information or planning the next step. This may be a change in design process related to the decrease in cognitive processes seen in designers exposed to DfI considerations, or a change related to the high effect size of certainty.

6.2 Implications of findings for Design Theory and Methods

Our findings suggest that design outcomes, specifically strength, mass, inspectability, and affective processes were not significantly changed by the addition of DfI considerations. We hypothesize that this may be due to the nature of the intervention and the DfX tool. New types of interventions may be considered for presenting DfI considerations. While the worksheet could be utilized further, instructional models or automated methods may also be used. In-class instruction similar to DfAM interventions by Prabhu et al. [69]

could be used to test the effect of longer interventions. Participation of groups such as The Learning Factory could lead to an intervention similar to the one by Booth et al. [62], which could help to show how considering inspectability repeatedly over an extended period could affect design outcomes. Once determination of $a_{90/95}$ becomes more efficient, an automated tool could be introduced to designers. Much like FEA during the redesign task, such a tool could be used to check if their design reached an inspectability goal. The methods used in Chapters 3 and 4 could be used in testing the impact of these interventions on design outcomes, as gathering 3D designs can become an automated process. However, methods in Chapter 5 may be too intrusive or labor intensive for measuring the effects of some interventions. For example, the think-aloud protocol likely will not work in a classroom or Learning Factory environment. Due to the nature of working with human subjects, consulting IRB is required for any future interventions and will likely help in the refinement of experimental designs.

Introduction of a new DfX framework provides opportunities for further publications. Expanding the framework to include more modes of NDE, like radiographic testing, requires collaboration with experts in academia and industry. In addition, the DfI framework will need to become one tool integrated with many others to help designers achieve better design outcomes. At the surface, the complexity achievable through opportunistic DfAM appears to be at odds with inspectability. However, designers will have to find balance between the two, which may require tools and techniques to appropriately manage. One solution could be a cost of quality tool [22,26,27], allowing designers to balance the value added through a complex feature with the cost it takes to adequately detect flaws. With such a tool, designers could make educated decisions on how to use the complexity available only through AM.

6.3 DfI in Industry

The results found suggest that further development of DfI considerations is needed before use industry. Industry professionals will want to know that incorporating the framework into their design practice will improve inspectability, reduce the risk of costly redesign, and not negatively impact other design outcomes. However, improvements to the DfI framework will be best made in collaboration with industry. Skilled designers familiar with geometries unique to AM, talented QA/QC professionals proficient with various modalities of NDE technology, and individuals whose expertise lies at the intersection of these fields can all help to improve DfI tools. Through structured interviews with experts, it may be possible to discover heuristics not discovered during the literature review from Chapter 3. In addition, observation of design practices in industry may help in the creation of design tools better suited to real-world applications.

The market for AM components continues to grow as the technology evolves and companies find new and innovative ways to utilize complexity that can only come from AM components. However, the growth of AM technology has outpaced standards. Designers should consider quality early in the design process so that companies can efficiently and effectively characterize parts. By keeping quality in mind early, designers can help companies to deliver safe and reliable safety-critical components to users in the medical, automotive, and aerospace industries.

6.4 Limitations and Future Work

Further research into DfI will help to create a base of knowledge and set of tools that enable designers to consider quality early in the design process. The number of participants was limited by the availability of designers familiar with CAD and AM at The Pennsylvania State University. Further recruitment, changing of requirements for participation, and expansion of sample population beyond Penn State are all viable methods to increase sample size. In addition, sample size of the task described in Chapter 4 may have been limited by social-distancing protocols, as students, staff, and faculty became hesitant of commitments during uncertain times. It is possible that recruitment may be easier once in-person instruction again becomes the norm.

Several obstacles arose because of social-distancing protocols which made data collection difficult. Relying on participants to provide their own computer, mouse, and internet connection, it was difficult to remove confounding factors. Internet connection issues caused one participant to drop out of the session twice during the redesign task. While connection was re-established both times in less than five minutes, it may have had significant impact on his emotional state and design process. Other participants experienced technical difficulties which required troubleshooting before the first task to resolve. With in-person testing, it may be easier to control for such factors.

Relying on participants to provide their own computer meant that we could also not control which CAD software was locally installed. For the purposes of this experiment, OnShape afforded a high amount of experimental control, since I was able to set up the project folders, the models, and the simulations. However, OnShape was not the preferred 3D modelling software for many participants. While some CAD skills may be transferrable, it is unrealistic to expect a person to pick up a new tool and be proficient after the 15-minute inspection task and 5-minute practice session. This likely impacted the quality of some designs as well as the mental workload and affective processes in some designers. While random sampling was used to avoid introducing any biases based on familiarity with the software, it may have impacted the results. In future, effort should be made to hold in-person design sessions on a computer maintained by the PI using a software familiar to all participants.

The results of inspectability analysis using static structural analysis, ultrasonic wave propagation simulation, and analysis using mh-1823 software showed no significant differences in the inspectability of components when DfI considerations were introduced. Since no significant differences were found in any of the other design outcomes, the lack of significance may be due to the small sample size. The method of using simulation may still be useful, as other tests have used similar simulations to determine the $a_{90/95}$ of a single part geometry [78,138]. To increase the sample size, design repositories such as the GE Jet engine bracket challenge repository could be used for simulating wave propagation and determining $a_{90/95}$.

Validation of results is required for simulation of ultrasonic wave propagation. This may involve the creation of geometries using AM technologies with known flaws, assessment using PEU, and the comparison of $a_{90/95}$ values determined experimentally and through simulation. The cost of manufacturing metal AM components is prohibitively expensive, meaning production of all geometries would not be possible. Instead, a sub-sample of parts could be created using metal AM. If simulation of defect detection is performed on one region of a component, production of a portion of the part can be done to reduce costs. In addition, geometric features which are difficult to simulate with dynamic explicit simulation should be identified, designed, and manufactured. Results of physically testing such components, including determination of $a_{90/95}$ experimentally, could be used to bolster existing simulations. Committing to collaboration between laboratories and universities is likely required for timely results.

Assumptions made to allow for efficient simulation of ultrasonic wave propagation need to be verified experimentally. First, 3-D models were simplified to 2-D cross-section to increase efficiency of simulation. Previous studies had made similar assumption with simple geometries [78], but validation of such methods with complex geometries will help to improve the accuracy and reliability of $a_{90/95}$ calculations. Second, all materials were simulated as homogenous materials, and white gaussian noise was added in post-processing to approximate scattering events that occur because of anisotropic grain structures. Through production and testing of physical components, the distribution and amplitude of noise can be characterized for materials commonly used in AM. Based on experimental results, simulation of $a_{90/95}$ can be generalized for a wide array of AM methods.

Inspectability considerations were limited to ultrasonic inspection to produce a tractable scope of work. However, inspection of complex components may require two or more NDT technologies to ensure parts meet all performance requirements. To provide designers with a comprehensive set of design tools, considerations will have to be developed for all available NDT technologies. Radiological methods were identified by the AMSC as another class of NDT technology applicable to the characterization of complex AM components [13]. Producing considerations for inspectability of components with radiological methods is the next likely step in creating a comprehensive set of DfI tools.

After considerations for radiological methods are created, considerations for other common forms of NDT like MT, PT, ET, VT, and dimensional metrology may be useful in considering inspection holistically. While these methods may not be appropriate for complex internal features, they may still be used in evaluating fit, form, and function at or near the surface of components. As nascent NDT technologies reach maturity, they should be evaluated for their applicability to evaluating complex AM components. If a technology is proposed that will fill any NDE gaps identified in the AMSC Standardization Roadmap, that technology is likely a good candidate for inclusion in the DfI framework. Continued development of inspectability tools and considerations will help the DfI framework to remain up-to-date and relevant as AM and NDT technologies continue to develop.

6.5 Conclusion

Using AM, designers can design components with far more complexity than was ever possible with traditional manufacturing approaches. Professional organizations such as ASNT and AMSC have noted the unique challenges such complexity poses to accurate and efficient inspection. To reduce cost of quality and avoid costly redesign, designers and engineers must keep QA/QC in mind early in the design process. The DfI framework is proposed to help designers produce components that are easily inspected. Studying the operating principles of ultrasonic testing, a popular NDE technology, a set of heuristics were created to increase the inspectability of components. Following develop of a new design tool, the DfI worksheet, two controlled studies were performed to determine how

DfI considerations may affect design outcomes and designers. Results showed that the intervention used to introduce DfI consideration may have had little effect on design outcomes. Continued development of DfI considerations, along with the development of new interventions, is important for helping designers to produce components easily inspected using mature NDE technologies. This work represents the first step toward a comprehensive Design for Inspectability framework. Continued research and collaboration with academia and industry will help in the development of knowledge and tools that will help designers create components that are easily inspected, reducing the cost of quality and ensuring the reliability of safety critical components.

Appendix

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