Creation and Assessment of a Novel Design Evaluation Tool for Additive Manufacturing

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ABSTRACT

Additive manufacturing (AM) is a rapidly growing technology within the industry and education sectors. Despite this, there lacks a comprehensive tool to guide AM-novices in evaluating the suitability of a given design for fabrication by the range of AM processes. Existing design for additive manufacturing (DfAM) evaluation tools tend to focus on only certain key process-dependent DfAM considerations. By contrast, the purpose of this research is to propose a tool that guides a user to comprehensively evaluate their chosen design and educates the user on an appropriate DfAM strategy. The tool incorporates both opportunistic and restrictive elements, integrates the seven major AM processes, and outputs an evaluative score and recommends processes and improvements for the input design. This paper presents a thorough framework for this evaluation tool and details the inclusion of features such as dual-DfAM consideration, process recommendations, and a weighting system for restrictive DfAM. The result is a detailed recommendation output that helps users to determine not only "can you print your design?" but also "should you print your design?" by combining several key research studies to build a comprehensive user design tool. This research also demonstrates the potential of the framework through a series of user-based studies, in which the opportunistic side of the tool was found to have significantly improved novice designers' ability to evaluate designs. The preliminary framework presented in this paper establishes a foundation for future studies to refine the tool's accuracy using more data and expert analysis.

Keywords: Additive Manufacturing, Restrictive, Opportunistic, Design Evaluation

1. INTRODUCTION

Additive manufacturing (AM) is rapidly growing in industry, academia, and medicine as a technology to both prototype and manufacture end products. In 2014, AM's market worth was around $4 billion and is expected to reach $23.33 billion by 2026 [1], [2]. AM offers many benefits when compared to traditional manufacturing (TM), such as geometric complexity, functional material grading and mass customization. Therefore, many designers and engineers are adopting or transitioning to the new technology in order to leverage its potential benefits for their products [3]. However, to ensure the maximum potential of these designed products, it is crucial that engineers consider design for additive manufacturing (DfAM). Though understanding of DfAM is evolving quickly, it is still considered an emerging field. Currently, TM processes still dominate in most industries due to high upfront costs of entering the AM product landscape and a general lack of knowledge in how to incorporate the AM technology into the design and manufacturing process [4]. Additionally, while creating complex geometries suitable for AM is possible, the current approaches require applicability that is not yet fully defined [5]. There is still ample room for expansion in using AM; in design contexts where it is appropriate, AM can be cheaper, faster, and more sustainable [6] than traditional subtractive manufacturing. Additionally, there is yet another realm where AM serves as simply one of numerous options to be considered alongside traditional manufacturing techniques. Such design with AM is beneficial when AM acts as an initial step on the way toward using more traditional manufacturing techniques (e.g., using material extrusion to create a form-and-fit test prior to investing in injection molding tooling). While not the central focus of this paper, design with AM serves as a relevant corollary to design for traditional manufacturing and DfAM.

Despite the AM spread, specific guidelines for new users still lack. Designers are challenged with a lack of knowledge of AM capabilities, process-related limitations and constraints and their effects on the final product. Because of this, there is a need for new methods to assist in selecting ideal AM process settings, associated materials, or appropriate designs for a given AM process [7]–[9]. This is further compounded by AM's growing popularity: a wide span of people, ranging from middle-school students to senior engineers, are showing interest in 3D printing. Both academia and industry need generalized guidelines [10]. With AM continuing to diffuse into many industries and STEM curricula[11], it is imperative that a comprehensive and effective tool is presented to novice designers to allow them to effectively evaluate parts. The design guidelines and tools that have long served TM processes may no longer be relevant or useful for AM because parts created using these new DfAM principles are geometrically contrasting to their TM counterparts.

The purpose of this research is to establish an initial framework capable of providing comprehensive guidance to novice designers in understanding the benefits and limitations of AM. The framework aims to achieve this by providing tailored outputs for individual designs through scoring systems and design recommendations. Though a range of design evaluation tools have begun to arise in research [3], they offer a piecemeal approach to design evaluation, often limited in the DfAM rules that they consider or in the AM process types that they incorporate guidance for. By developing a more comprehensive approach that can accommodate a range of AM process types along with an expansive view of DfAM, the likelihood of successful and meaningful prints should increase. This framework is then evaluated through an initial user-testing study where both novice and expert designers evaluate a series of designs for AM appropriateness with and without the proposed tool. The output scores from the use of the framework are compared to the self-evaluation scores without the framework to determine (1) consistency across expert groups, (2) if the novice group is collectively advanced towards the expert group, and (3) if the novice group's internal consistency is improved. These results will be presented and discussed, with potential future work outlined.

2. RELATED WORK

Design for AM literature has emphasized the need for a shift in design thinking when utilizing AM processes over traditional manufacturing processes. Research has outlined that product innovation and design methods that were previously used need to be revamped to be applicable to the AM procedure [12]. Initial research observed the trend of AM moving towards end product manufacturing and the need to reconsider traditional design methods during or before the initial design stage [13]. With the unprecedented possibilities that AM offers as well as the added limitations, it is crucial to recognize that conventional design for manufacturing steps may hinder the advancement of AM within the design space.

2.1 Considering the Duality of DfAM

While traditional design for manufacturing approaches tend to guide designers in side-stepping the limitations inherent in traditional manufacturing processes, DfAM, by contrast, challenges users to consider both the opportunities and restrictions that AM poses to design. Laverne et al. [14] identified these two sides of DfAM and was the first in defining the concept of Restrictive DfAM (R-DfAM) and Opportunistic DfAM (O-DfAM). Within the design making stage, traditional design for manufacturing methods do not apply to the AM design process and new methods are essential in the creation of innovative design solutions. R-DfAM has been emphasized in a significant amount of ongoing research and aims to outline AM-specific limitations and presents design rules that ensure manufacturability [15]. R-DfAM can be seen as a set of guidelines that maximizes the quality and expected outcome of a print by accommodating process limitations. These limitations are inherent in the fundamental difference of layer-wise manufacturing when being compared to conventional subtractive processes [16]. However, limitations within AM vary process-to-process due to the fundamental differences in the technologies. For example, the consideration of support materials in overhangs or self-supporting angles is negligible when dealing with most powder-based processes as layers are being supported by loose powder [17], [18] whereas in material extrusion supports must be present to hold up deposited layers of material. Conversely, access to cavities or crevices may be a greater design concern for powder-based than other processes due to the presence of loose powder during the print.

On the other side, O-DfAM is a series of considerations intended to lead designers to optimize their part and leverage the benefits of AM. AM offers an array of opportunities that was not previously possible with TM, such as utilizing generative design tools (topology optimization, lattice structures, biomimicry), mass customization, and monolithic multi-material structures [19]. Despite the benefits AM has to offer, its consideration in the design space is currently limited in contrast to R-DfAM which may hinder the overall adoption of AM. This can generally be attributed to a lack of knowledge in how to fully integrate and optimize the process into existing work flows [20], generally requiring designers to understand when their design is worth creating with AM. Similar to R-DfAM, various processes can offer varying opportunities. For example, embedding components is possible for low-temperature processes such as material extrusion, but high temperature processes such as DED are not able to take advantage of this feature [21].

A dual-DfAM approach combines the concept of both "*should I print this*" (O-DfAM) and "*can I print this*?" (R-DfAM) to consider both sides of this new design thinking. This dual-DfAM design approach is holistic in that it encourages designers to maximize the utility of AM while considering the limitations within the design space. Pradel and coauthors offer one of the most extensive investigations of how such dual-DfAM currently manifests across the field of DfAM study [22]. They performed a critical review of 81 articles to establish a framework centered on the role of DfAM when considered across a generic design process, including in the conceptual design, embodiment design, detailed design, process planning, and process selection stages. Despite the significance for innovation, dual DfAM methods only account for approximately 30% of existing DfAM methods in research [14]. However, the benefits of dual-DfAM consideration are becoming clearer. For example, in educational settings, students trained in dual-DfAM produce more useful, unique, technically good and overall creative designs than those with only R-DfAM education (within a competition-structured DfAM task) [23]. Despite the quantity of research in presenting and demonstrating the importance of rethinking design in the face of AM, there lacks a methodology to support designers in comprehensive consideration of dual-DfAM when evaluating the suitability of designs for AM.

2.2 Existing DfAM Evaluation Approaches

There are several emerging design tools that accommodate the growing need to support novice AM designers in the evaluation of candidate parts for printing. However, these tools often provide narrow process scopes and focus on either the opportunistic or restrictive side of AM rather than utilizing a holistic approach with dual-DfAM.
Certain tools allow designers to evaluate their designs through a rapid, intuitive scoring system. Booth [10] presents a tool to allow user to quickly analyze printability of designs in order to reduce the number of printing and prototyping failures. The user is presented with a physical worksheet that prompts them to interact with 3-point or 5-point scales, with a predominant focus on R-DfAM elements. There are 8 elements of which each element is equally weighted. The user sums their selections and utilizes a key to determine the necessity of redesign. There are elements of opportunistic evaluations present with certain starred ratings indicating consideration of a different manufacturing process, but there is no direct ranking of the opportunistic side. After the worksheet was implemented, both the rate of print failures and reprinted parts fell roughly 40%. Bracken [24] presented a similar tool catered specifically towards Powder Bed Fusion design analysis. The user is presented with a three-point scale in which they score either 1, 3 or 5 depending on how restrictive their design is. This worksheet freely uses specific values within the questions as it is catered towards a single process. When utilized in a design workshop, 77% of respondents either agreed or strongly agreed that this worksheet was useful for design for AM.

On the other end of the spectrum, there are tools that cater towards the opportunistic side. As an example, design heuristics cards can be used to educate designers on how to take advantage of O-DfAM to improve their designs [25]. These heuristics include a series of figure and text-based cards to inspire designers with process-independent design methods to maximize the capability of AM during the idea generation stage. The cards present case studies as well as a description of each opportunistic element. Such heuristics positively impact the generated designs by novice designers and are found to be more effective at communicating DfAM concepts in the early phases of re-design than a lecture on DfAM alone. A similar approach by Perez [26] presents users with design principles containing textual descriptions, simplified visuals and a real world example. In early-stage design, the cards were found to significantly improve the quality and novelty of users' ideas and assist in innovative ideation. Additional studies showed the effectiveness of these cards in producing significantly improving the novelty and quality of ideas [27].

Computational and automated tools have also been presented to cater to this growing need of early stage design evaluation for AM. Kumke [15] presents a criteria-based evaluation tool which recommends appropriate design methods in the context of conceptual DfAM and is further aided by digital and physical models to assist in visualizing the design concepts which simplifies the Semantic network of the wide array of AM design potentials. Novice participants in a design workshop, however, perceived this tool to contain too much design information and may be overwhelmed. Yang further extends the idea of automating the identification of relevant AM part candidates [28]. Specifically, machine learning was used to establish a more efficient screening system that reduces the experience-dependency seen in other decision support systems. Many emerging frameworks aim to provide process recommendations to the users, but require post-design knowledge such as production quantity [29], material cost [30] or surface roughness [30], [31] which limits the user accessibility and further complicates the approach for novice users. The fundamental dual-DfAM design approach presented will be utilized as a foundation for how the tool is constructed and previous DfAM evaluation approaches will be utilized to provide inspiration and support for various aspects of the tool.

As presented, there are a variety of approaches and growing research in the field of DfAM education and design analysis tools for AM. Generally, the research and approaches have targeted specific areas of DfAM, such as the DfAM heuristics (O-DfAM) or the Booth worksheet (R-DfAM). However, there is yet to be a comprehensive approach that combines the benefits of previous work to give designers a holistic and easy-to-use tool to evaluate both *can* a part be printed and *if* it should be printed. The next section outlines a novel framework for such a tool.

3. PROPOSED DECISION FRAMEWORK

This paper presents a solution for a framework that builds upon prior research and improves upon the previous points in Section 2. The solution assumes users to be AM novices or perhaps intermediate users of AM technologies; that is, users who understand the basic concepts behind AM, especially for the material extrusion process, but lack extensive understanding of DfAM. Given a design tool generated from the proposed framework, this solution further assumes that users can manipulate, visualize, and select the appropriate options on the tool with little to no difficulty and does not thoroughly accommodate for those users who may face difficulty in working with the tool. These assumptions, though limitations of this work, were necessary considerations to incorporate key features that enable interactive, self-guided, and holistic DfAM decision making. Specifically, this proposed framework aims to incorporate the following features to support the DfAM decision making process:

- Dual-DfAM Approach: Implement both restrictive and opportunistic elements to utilize a Dual-DfAM approach for a more holistic evaluation if AM is an appropriate approach.
- Weighing System – Features: Implement a weighting system that more accurately evaluates the importance of each design element rather than assuming each element is of equal importance.
- Weighing System – Process: Implement a weighting system that accounts for variation in elements across process types rather than assuming each element is of equal importance between different processes.
- Process Agnostic Language: Implement a set of questions that relate to elements using process-agnostic language to ensure the tool has a wider usability.
- Feature Based Evaluation: Leverage a feature-based approach that enables a wide range of use cases by focusing predominately on the geometry of the design rather than the way in which it is being used.
- Inclusion of Visual Aids: Increasing the user engagement and detail of the tool by providing manipulable 3D models as detailed and clear visual aids to accompany each response level in a question.
- Transparent Design Recommendations: Generate a series of detailed redesign recommendations based on user input to provide score transparency and informative outputs.
- Standalone Digital Framework: Integrate all the above features into a single approach via a digital application. This also enables automation of any required calculations to increase simplicity and increase usability.

Each of these features, as well as how they are both measured and determined to be successful, are collected in Table 1. Additional detail on each feature is presented in the subsections that follow. The high-level structure of the framework that encompasses these features is shown in Figure 1. It outlines the major segments of the framework that enables an input design to be evaluated and scored.

Table 1. Identification and Evaluation of Framework Features

Framework Feature	Evidence of Inclusion	Success Threshold
Dual DfAM Approach	Number of questions related to each O-DfAM and R-DfAM	Less than 50% difference in number of O-DfAM and R-DfAM questions
Weighting System – Features	Quantitative feature weighting value associated with individual R-DfAM questions	**All** R-DfAM questions have a weighting value associated with them
Weighting System -- Processes	Quantitative process weighting value associated with individual R-DfAM questions	Each R-DfAM question has a weighting value for at least 5 of the 7 main AM process types
Process-Agnostic Language	Multiple-choice questions with absence of quantitative values	3+ response levels offered as options for each question
Feature-Based Evaluation	Questions can be answered without context beyond the provided geometry	**All** O-DfAM and R-DfAM questions can be addressed through the geometry
Inclusion of Visual Aids	Manipulable visuals accompany the R-DfAM and O-DfAM questions	**All** questions include 3D visuals of each response level and can be rotated at minimum 360 degrees in the XY
Transparent Design Recommendations	Final output includes numerical percentage and plain language recommendations	O-DfAM and R-DfAM categories each result in a score between 0-100% that is explained in plain language
Standalone Digital Application	All framework features are combined into a self-contained digital application	Digitized framework requires **no external feature dependencies** to make informed DfAM recommendations

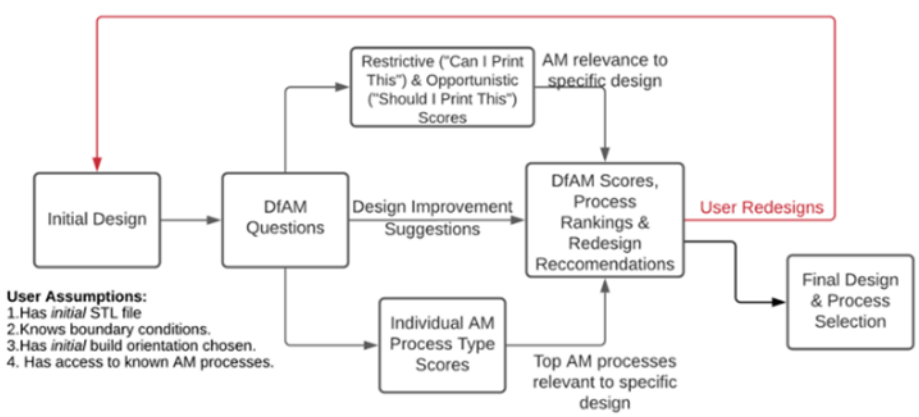

Figure 1. Overall framework flow.

As shown in Figure 1, the user starts with their early-stage initial design. The fidelity of the provided design is flexible, though the initial assumption in the framework is that the designer can provide a preliminary STL file. The design features are evaluated in the framework via an R-DfAM question set and then an O-DfAM question set. The user can respond to each question using a 3-point scale which determines the design's suitability along the spectrum of R-DfAM and O-DfAM. As the user enters each response, the framework calculates R-DfAM scores, O-DfAM scores and after the last question a final Restrictive score and an Opportunistic score is output to the user to indicate the relevance of AM to their design input. In answering each question, the framework simultaneously generates specific design improvement suggestions based on the user's input for each question. Lastly, in utilizing a pre-determined weighting system for AM processes, specific processes are ranked and recommended to the user for their design. Final recommendations compiled and output to through in a digital format. Based on the tool output the user can choose to either redesign the part and restart the process or proceed with the print. The following subsections present each of the key features inherent to the novelty of the approach and provide additional detail to support its relevance to the proposed framework.

3.1 Inclusion of Dual-DfAM

Laverne's study [14] presented that dual-DfAM methods are the most suitable within an innovation context as they are correlated with a systemic level of product description. Prabhu [23] concluded that in a study, students with dual-DfAM knowledge generated ideas with *"higher technical goodness and overall creativity compared to the showcase-structured task."* Considering this, it is important to establish a framework that evaluates using a dual DfAM approach.

While it is crucial to educate and inform the user on if their print can be printed within the confines of AM limitations, it is also very important to realize that there are often cases in which AM is not the ideal manufacturing method to use. To account for the needs of both R-DfAM and O-DfAM, the proposed framework includes the 17 dual-DfAM considerations presented in Table 2.

Table 2. Dual-DfAM Considerations Included in Framework.

Restrictive DfAM	Opportunistic DfAM

Internal Access	Geometric Complexity – Freeform/Organic Structures
Unsupported Features – Overhangs	Geometric Complexity – Lattice Structures
Unsupported Features – Bridges	Customization
Unsupported Features – Self-Supporting Angles	Part Consolidation – Monolithic Assemblies
Cross-Sectional Geometry – Sharp Corners	Part Consolidation – Assemblies with Relative Motion
Cross-Sectional Geometry – Size/Area	Multiple Materials
Small Features	Embedded Internal Components
Cross-Sectional Ratio	
Surface Accuracy	
Structure Anisotropy	

The considerations featured in Table 2 were selected through consideration of previous R-DfAM and O-DfAM tools presented throughout this paper, as well as previous work performed by the authors of this paper. Upon validating the proposed framework, future work may derive more restrictive and opportunistic DfAM concepts from other established tools to improve Table 2. In addition, Table 2 omits advantages related to the economic benefits of small batch sizes in AM so that the considerations remain, crucially, functionality-independent; this ensures a feature-based approach, where the evaluator does not necessarily need to know the actual use case for the final product, only the information that is contained in the STL file.

3.2 Feature-Based Approach

To maximize the tool's generality, users score their designs on the absence or presence of geometric features rather than how the design will be applied in use. Such feature-based approaches are demonstrated in prior DfAM research. Zhang [32] presents a multi-attribute decision making process in which part orientation is optimized and examines a ranking method based on expert evaluations and accommodates individual user requirements. Similarly, Tedia [33] presents a method in which a three-dimensional voxel array is evaluated for infeasible features, minimum feature size, support material, orientation and manufacturing time for different build orientations and was successful in accurately analyzing build time estimations utilizing its feature-based approach.

By establishing the proposed framework around a similar feature-based approach, this ensures that the tool is context-agnostic and can be applied to a wider array of designs. By removing context of a design's use, it does not confine the tool and its' questions to specific conditions, and it enables anyone within a product cycle to evaluate a design's printability. However, emphasizing only a design's geometric features in the evaluation framework is not without its limitations. By removing the use case consideration, you may limit the scope as to how appropriate AM is for a specific design.

3.3 Question Language

Each question in both the restrictive and opportunistic section presents a different element for the user to analyze their design. The question inquires the user on the presence of specific features present in their design. Since this tool is being developed to be accessible by AM novices, certain questions have additional descriptions that explain what the elements mean to reduce any knowledge barriers.

Previous approaches have incorporated both 3- and 5-point scales for user input [10]. This tool presents a solution in which the user is presented with a 3-point scale (with answers nominally denoted as a, b, and c) for every question presented to the user. Owing to those previous approaches, and other use of scales in similar tools [24], this tool maintains a similar structure for the questions which provides sufficient resolution for early-stage design. Each restrictive question follows a general format of answer option *"a"* increasing the difficulty of the print success and answer option *"c"* reflecting minimal effect on printing difficulty as shown in Figure 2.

Unsupported Features – Overhangs
Q2: Does your part have overhangs? Overhangs are geometries that stick out mid-air and are only supported on one end.

a. The part generally has long overhanging features
b. The part generally has short overhanging features
c. There are no overhanging features

Figure 2. Restrictive question example.

While previous research into evaluation worksheets have opted for specific numerical values throughout the R-DfAM evaluation questions, doing so limits the tools applicability to the wide range of available AM processes. As such, the language used in this framework avoids specifying certain metrics that may be process specific, as shown in Figure 2. However, when general consistency exists across processes, a numeric value can be utilized to define an initial boundary for the user while still maintaining a scope to maximize process agnosticism.

The opportunistic questions follow a similar format (Figure 3) in which answer option a does not leverage the benefits presented by AM and answer option *"c"* maximizes the benefits of AM. Again, the language and structure of these questions are presented in a way that does not actively focus on a single process. The language here not only provides relevance to the question but guides the user in the DfAM process.

Geometric Complexity – Lattice Structures

Q12: Does your part leverage the geometric complexity offered by AM such as internal lattice structures?

a. The part is comprised of fully dense, continuous material.
b. The part uses lattice structures to reduce material use in areas with minimal loading.
c. The part relies heavily on lattice structures throughout, with density adjusted based on loading.

Figure 3. Opportunistic question example.

3.4 Interactive Models

Another key factor included within this framework is the refinement of the visual representations of each option. Previous restrictive DfAM worksheets present a solution in which the focus of each element is presented via text, with low-fidelity sketches to serve as a visual aid [10] [24]. Design heuristics cards focus more on the visual aspect with more detailed, colored, and real-world examples to convey each opportunistic element at a high level [25].

The approach presented in the current paper attempts to bridge the benefits offered by existing tools and further refine the advantages of visual aids as both an educational tool for novices and one that clearly communicates the definition of each element and option. Visual learning has been extensively studied and proven to promote user interaction, improve information retention and increase content clarity. Presentation modalities for heuristics are explored and research [40] has shown when given 3D models representing modalities, experts were shown to produce higher novelty redesigns of parts. These studies motivate the focus on presenting clear and concise visuals within the early-stage design process.

As shown in Figure 4, the framework presents the user with 3D models that correspond to each answer choice. A specific model was generated and modified for each answer choice to provide a unified example for each question. These models were generated internally by DfAM domain researchers to represent an idea of the final application. They provide the user with a clear and concise representation of the element to reduce ambiguity and allow the user to interpret each element quicker. These models can be interacted with by the user, which allows them to pan, zoom and rotate around the build plate.

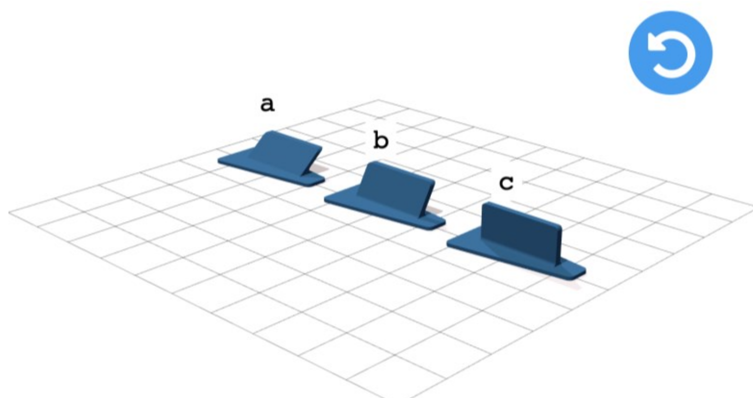

Figure 4. Interactive model example.

This added layer of interactivity presents additional information to the user and may create a more engaging tool. Alvarez [34] showed that for a specific academic class, 100% of the students were satisfied with the inclusion of 3D models in their learning environment and believed they were useful to their education. Similarly, Taleyarkhan [35] investigated the impact on students' CAD utilization in design projects and found that the utilization of this method helped individual students progress from beginner designers towards adept and informed designers across several design strategies by exploring concepts through a three-dimensional space. This previous work supports the benefit of including 3D models within the framework to complement the existing renders shown previously.

3.5 Scoring

The scoring systems from previous worksheets assume that each DfAM element has equal importance when determining print success. This framework differs in that a weighted system is incorporated between elements. Due to the technical limitations and benefits of certain processes, it cannot be assumed that when observing the entire AM landscape, each design consideration is of equal importance across different AM processes. For example, with powder-based processes such as binder jetting, there is a minimal design consideration for support structures because the loose powder supports each layer [17] whereas with most other processes support structures are required due to the method of deposition [36]. Furthermore, within the process itself, the design considerations may vary in importance. With binder jetting, support structures require minimal consideration within the design stage. However, since the process is powder-based, improving internal access requires greater design consideration within the context of just binder jetting [37]. Therefore, it is important to build a tool that both considers every process and accommodates the differences between considerations, it is important to construct a weighting system.

To further investigate this process variation and to identify preliminary weights for a range AM processes, a survey was internally distributed to a series of AM domain experts. They were asked to identify the AM process they considered themselves to be an expert in and independently weigh each restrictive element found in Table 2 from 0-10 for their chosen process, where a score of 10 denotes a restrictive consideration that is essential for a given process and a score of 0 suggesting that the consideration is not at all important. After all scores were collected from each expert, all scores for each restrictive element were averaged across process types to arrive at the values shown in Table 3. In this way, the average score for the restrictive element acts as a signifier for how important that element is broadly considered to be by experts across all AM process types. Despite being an average score for all process types, for the initial testing of this framework, the values shown in Table 3 are utilized for the restrictive scoring. As the table shows, there is variation across the AM landscape for various restrictive elements. Unfortunately, in the current DfAM landscape it is difficult to recruit domain experts across all seven main AM process types, especially for those processes that are less commonly utilized (e.g., sheet lamination). Because of this, the values in Table 3 are an average of expert assessments across all process types (i.e., the restrictive scores of powder-bed fusion experts were also averaged with those of material extrusion experts). Though this limits the usefulness of the tool in identifying restrictive DfAM nuance between processes, the fundamental approach underpinning the collection and use of these weights presented in this study can be used to expand the collection of inter-process data in future work. Although these scores are preliminary and would require more data to accurately represent the elements, the initial values already demonstrate the need to account for restrictive DfAM variability across AM.

Table 3. Results from expert analysis AM study.

Restrictive Element	**Average Weighting Factor**
Improving Internal Access	6.57
Increasing Minimum Feature Size	6.30
Reducing Overhangs	5.78
Reducing Bridges	5.87
Increasing Self-Supporting Angles	5.35
Increasing Surface Accuracy	5.33
Reducing Structure Anisotropy	5.22
Increasing Cross-Sectional Ratio	4.70
Reducing Cross-Sectional Area	4.35
Reducing Sharp Corners	3.79

3.6 R-DfAM Scoring Weights Implementation

The proposed framework begins with evaluation of R-DfAM considerations. The overall flow of this section is outlined in Figure 5. It outlines the tool's process at each question where the user's answer (*a, b, or c)* multiplies the overall restrictive score (Table 3) for that question and the individual process scores for that question, and continuously sums the scores throughout the restrictive section.

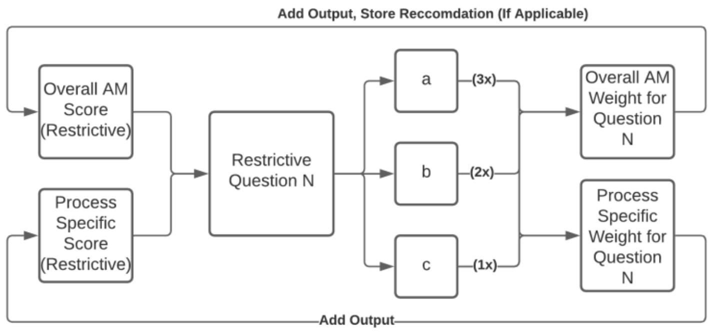

Figure 5. Restrictive flow.

As the user selects each option (*a, b, or c)* which corresponds to an answer score (1, 2 or 3). This answer score is multiplied with the expert weights (Table 3) for that specific question to produce a weighted answer score. For example, if the user selects *b* for *reducing overhangs,* that question will have a score of 11.56 (5.78 * 2). As the user continues to answer each question, the output of each question is cumulatively summed each time, until they submit the last restrictive question. To output the value as a percentage ($R_{\%}$) to the user, the value is normalized between the minimum and maximum possible sum of weighted scores, where the minimum score (R_{min}) is determined by answering *c* for every question and the maximum score (R_{max}) is obtained by answering *a* for every question. Equation 1 shows this calculation.

$$R_{\%} = 100 - \left(\frac{R - R_{min}}{R_{max} - R_{min}} * 100\right) \tag{1}$$

Simultaneously, the individual process scores obtained through the survey are multiplied by the same answer score (1, 2 or 3) and cumulatively summed after each response. This will output a list of raw summed scores for each process which are then ranked (from lowest sum to highest) to recommend processes to the user.

3.7 O-DfAM Process Elimination

Unlike the restrictive elements, which incorporate an expert-derived weight for each question, each O-DfAM question specifically has an equal weight. The reasoning behind the different approach for this is that O-DfAM has no clear hierarchy of importance because it has no objective measure of print success, unlike R-DfAM, where direct causality can be established between design features and the likelihood of build failure. Figure 6 displays the overall flow of the opportunistic section of the framework.

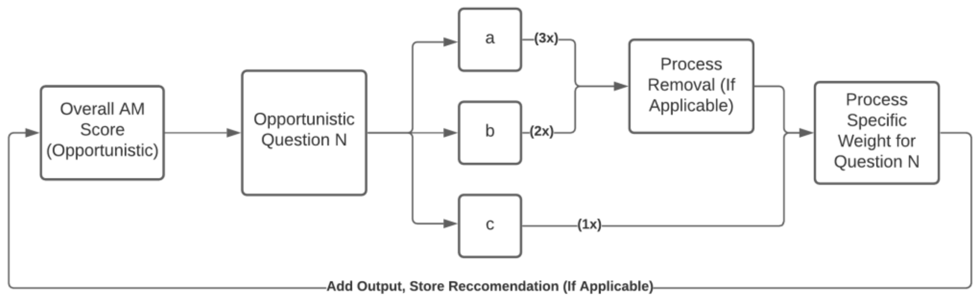

Figure 6. Opportunistic flow.

Though it isn't subject to the same weighting scheme as restrictive, there is still the potential that a particular AM process might be removed from consideration due opportunistic elements not being technically possible or feasible using a specific AM process. Table 4 displays processes that are removed in this tool at specific questions, with references for each process.

Table 4. Process removals during opportunistic analysis.

	Multiple Materials	Embedded Internal Components
Processes Removed	VP [38] BJ [39] PBF [40]	PBF, DED [41]

3.8 Numerical Recommendation Ranges

As described earlier in the section, the tool outputs percentage scores to the user for both R-DfAM and O-DfAM. To assist in the evaluation of their design, the framework output also includes a key as with previously published worksheets [10], to help the user interpret the meaning of these percentages.

The following is presented for the restrictive section:

- 0-59% Major redesign required
- 60-79% Some redesign required
- 80-100% Will likely print with few issues

The following is presented for the opportunistic section:

- 0-19% Consider other processes/adding features
- 20-29% AM is a good candidate
- 30-100% AM is a great candidate

The above values are a preliminary estimation of what might be presented to the user. The values themselves are indicative of the current climate of DfAM, in which R-DfAM dominates and O-DfAM has a much lesser consideration in the current design space [14]. In Section 4, an initial study reveals a more empirical presentation of this scale, as well as a potential method to produce these values.

3.9 Digital Format

As presented throughout this section, there are various features that are included in this tool. To maximize usability and interactivity, simplify the tool, and effectively include each attribute, a digital format is the ideal way to communicate each of the previous tool functionalities to the user. To produce a prototype, a concept was produced via Qualtrics, an online survey builder. Custom HTML, JS, and CSS were injected into the survey to provide all the required components. Figure 7 displays the UI presented to the user.

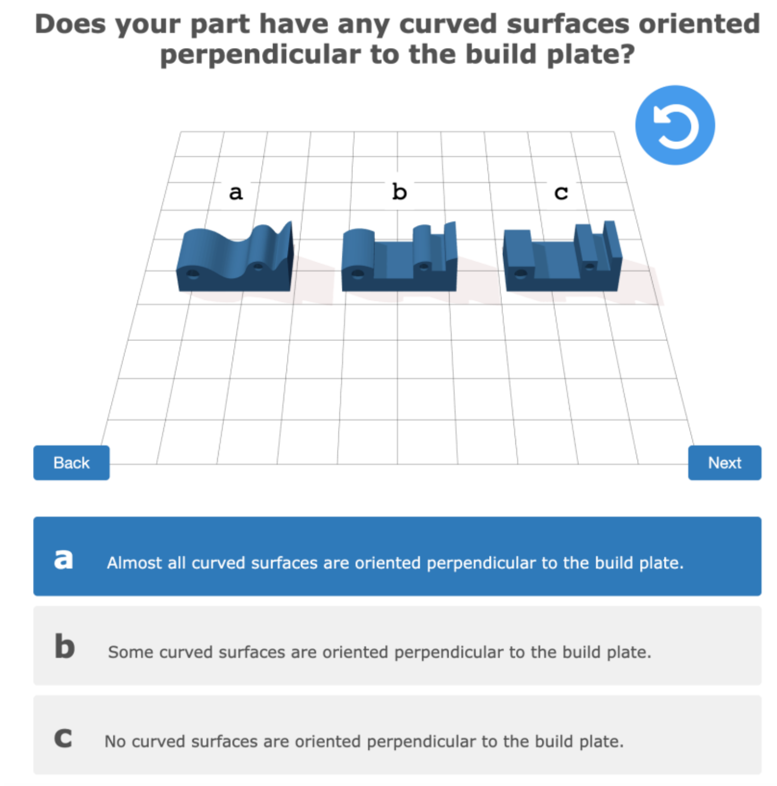

Figure 7. DfAM tool user interface with 3D models.

From a front-end perspective, the digital app allows the user to interact with each question, one at a time, to allow them to focus on each element individually. This added layer of interactivity with a digital tool can produce more positive learning motivation and more positive effects on learning outcome [42]. Furthermore, cognitive fit theory proposes that when the representation (information visualization) of a problem more closely fits the problem-solving task, there is an improvement in the accuracy and speed of the problem/decision-solving process [43]. The higher accuracy of visualizations through clear images and 3D models will provide greater detail that will allow designers to more accurately problem solve within the design stage.

Furthermore, in digitizing the tool, it is possible to automate the variety of added calculations that are being included in the framework allowing the user to focus on the primary task. Additionally, the generation of the output (workable DfAM scores, ranked process list and potential re-design recommendations) can also be generated, providing the user with a practical and straightforward result. Potential outputs are shown in Figure 8, in which a positive restrictive and negative opportunistic score is shown, with a plain language presentation of the score's significance.

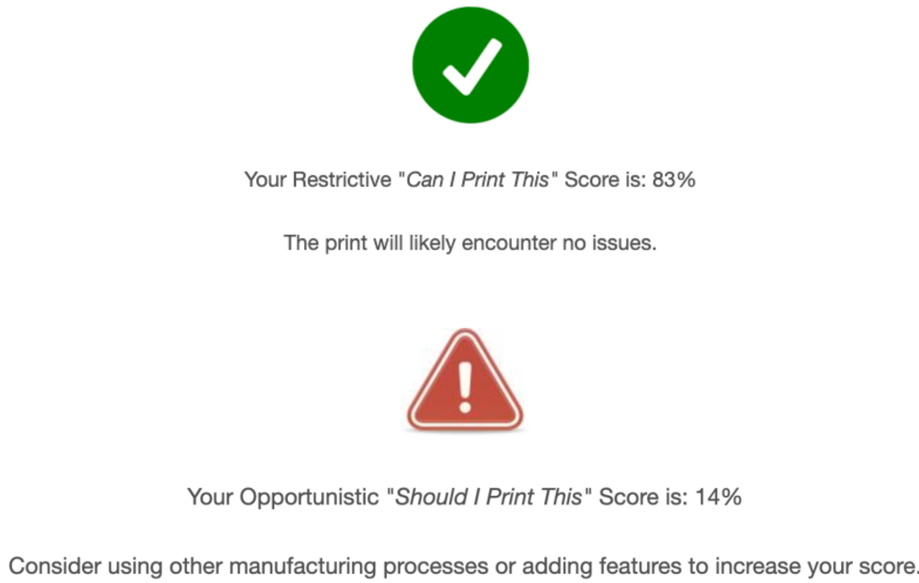

Figure 8. Example of potential tool output.

This section has provided a detailed overview of a novel design evaluation framework. It builds upon previous literature and combines various approaches to provide a comprehensive tool for novice designers to accurately determine if their part can and should be printed. It provides features not previously represented in a tool of this nature, with a digital interface, dual-DfAM approach and expert weighting system. However, there is still a need to robustly validate the usefulness of the tool through user studies, in a way that most existing tools have not yet been validated.

4. FRAMEWORK APPLIED IN PRACTICE

Given the existing body of research, and the proposed design tool structure presented in Section 3, it is crucial to evaluate the effectiveness of the tool when evaluating designs to be additively manufactured. An experiment was developed to test the effectiveness of the proposed digital DfAM tool. The experiment consisted of two parts: (1) a control survey in which participants were shown a series of designs and asked to evaluate how appropriate each design was for AM and (2) a survey in which different participants were shown the same designs and asked to evaluate the designs using the proposed digital DfAM tool detailed in Section 3. The study was reviewed and approved by the Institutional Review Board, and implied consent was obtained from the participants prior to the experimentation. Both surveys included a pre-survey demographic collection in which participants were asked to provide demographic data as well as information regarding their experience with AM.

4.1 User Study Design

To accurately evaluate the hypotheses, the study required responses from participants in both the novice and expert levels of AM for the two surveys (with and without the use of the DfAM tool). The novice pool was obtained from first year engineering students from a large northeastern university, while the expert pool was expanded to universities and institutions worldwide, given the challenges associated with identifying a sufficiently large expert pool at a single institution. To identify a participant's expert level, the following prompt was given within the demographics section of both surveys: *"Select the option that most closely resembles your comfort level with 3D printing:"* with the following experience level options (this scale has been validated in a previous research study [44]):

(1) I have never heard about 3D printing
(2) I have some informal knowledge about 3D printing
(3) I have received some formal 3D printing training
(4) I have received lots of formal and/or informal 3D printing training
(5) I am an expert in 3D printing and can proficiently manufacture parts

Table 5 displays the responses for both surveys by experience level. At this point the distinction between expert and novice was made that responses 1 - 3 represented the novice class and responses 4 and 5 represented the expert as early survey responses indicated very few individuals who met the first group criteria, with most individuals having a general understanding of the concept of AM. While the number of responses in Table 5 may appear to be unbalanced across the two surveys, the DfAM tool survey required a greater investment from participants than the control survey and thus generated collected fewer design evaluations per respondent. It is important to note that the survey does not ask evaluators to describe which AM process types they are basing their responses on; it is likely that many respondents, especially at the lower levels, are basing their knowledge entirely on the material extrusion process. Such knowledge may not fully translate to other AM process types, which could affect the results of the tool's deployment. In future work, the research team will look to expand the amount of detail to be supplied by evaluators to better understand which process they may be envisioning when conducting their evaluation.

Table 5. Survey Respondent Totals

	Control Survey	DfAM Tool Survey
Novice Total	90	217
Expert Total	44	68

A series of 24 designs were produced for use across both surveys. The designs were self-rated by participants in the control survey and the same set of designs were presented to the second group of participants in the DfAM tool survey. The designs were presented to the participants in the form of a manipulable 3D object.

The first 12 designs varied elements that correspond to restrictive DfAM and the latter 12 varied opportunistic elements. The designs were first presented to and reviewed by a group of AM experts. To capture a wide variety of design feedback, the degree of restrictive and opportunistic DfAM varied across all the designs, presenting some participants with a design that would be suitable for AM and some with a design that would not be. Figure 9 shows example designs of varying levels of quality from both the restrictive and opportunistic sets.

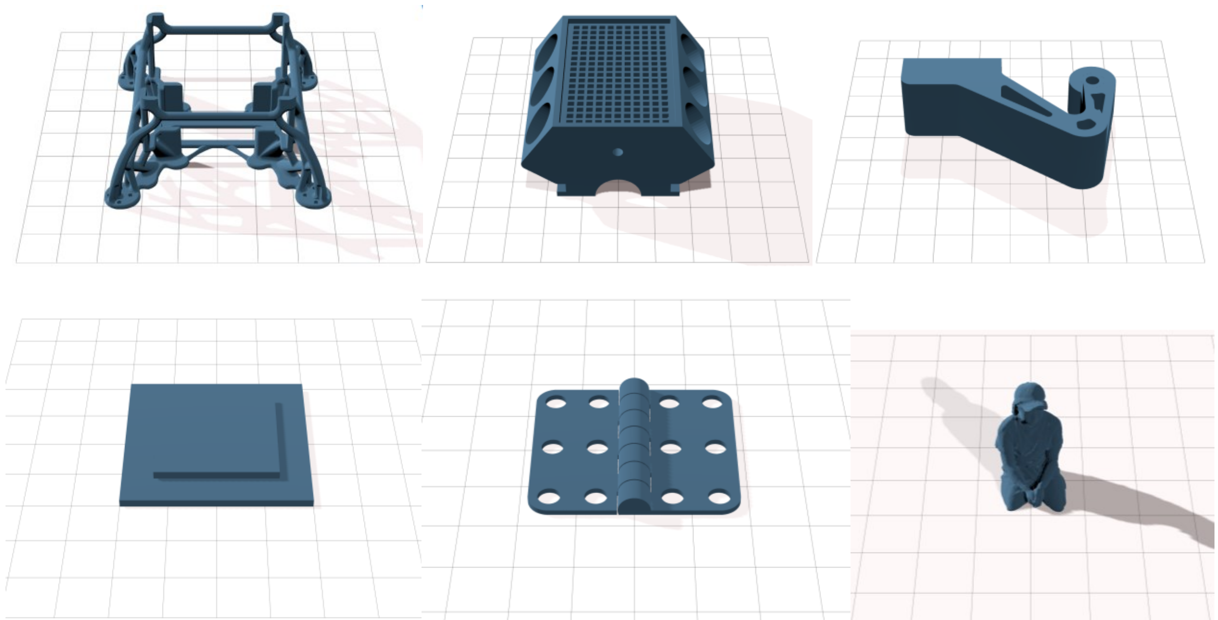

Figure 9. Examples of restrictive (upper 3) and opportunistic (lower 3) design examples

4.1.1. Control Survey

The control survey was developed to evaluate how both novice designers and expert designers evaluate parts to be 3D printed without the aid of the proposed digital DfAM tool. With this data, the variation within the novice and expert designer groups can be evaluated for specific designs as well evaluating the difference between the novice and expert groups for those designs.

Participants were shown and asked to rate a set of 4 designs relating to restrictive design elements and a set of 4 designs relating to opportunistic elements, providing 8 data points per participant. The order in which the restrictive and opportunistic sets were shown to participants was randomized to reduce order bias. Participants were shown each design one at a time and prompted the user to rate the design on either a restrictive design scale or opportunistic design scale. The participants were informed to answer questions specific to material extrusion; a brief description of the technology was included for novice participants. Figure 10 displays an example of a question presented to the user – the left shows a restrictive question, the right shows an opportunistic question. The user is shown a design which they can rotate, zoom, and pan in 3D space to fully understand the geometry. Participants are asked to evaluate the design with 3 options. The language utilized in these options and the number of options is identical to that of the output of the digital DfAM tool, as discussed at the end of Section 3. This allows a more direct comparison of the control survey with the DfAM tool survey.

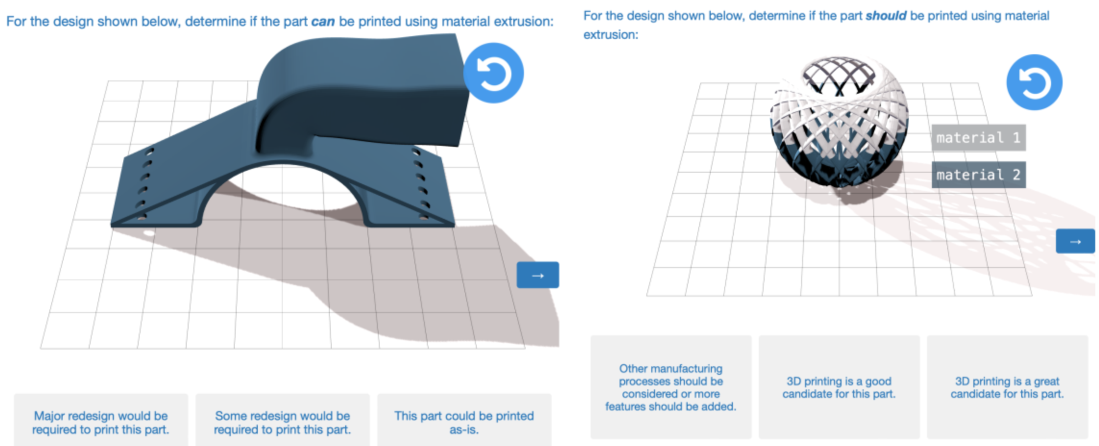

Figure 10. Example of restrictive(left) and opportunistic (right) question presented to user

4.1.2. DfAM Tool Survey

The DfAM tool survey was developed to evaluate how both novice designers and expert designers evaluate parts to be 3D printed with the aid of the proposed digital DfAM tool. Like the control survey, the variation within the novice and expert designer groups can be independently evaluated for specific designs as well evaluating the difference between the novice and expert groups for those designs. This will then allow an evaluation to determine if expert analysis remains consistent with and without the design tool, if variation within the novice group is reduced when using the design tool, and if novice design ratings are more consistent with expert design ratings when introducing the design tool.

The DfAM Tool survey was developed by modifying the digital DfAM design tool to include designs from the set of experimental set on the inset, picture-in-picture on the side the survey screen. The same demographic questions were presented to the participant as well as a brief pre-survey tutorial and explanation of the overall interface and designs that the user will be rating. Each participant was introduced to a design from the restrictive set and then answered the 10 restrictive questions. An example of a question presented to the user is shown in Figure 11. Once completing the restrictive portion, the participant was introduced to a design from the opportunistic set and completed the 7 opportunistic questions from the design tool.

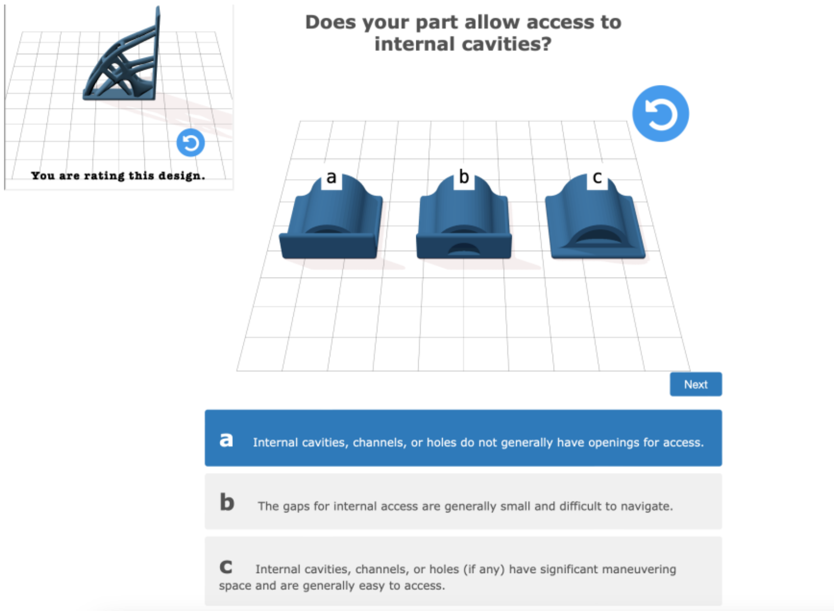

Figure 11. Example of DfAM tool survey question presented to the user

4.1 Results of User Study

The data collection took place over a period of 2 months. The control survey collected 536 restrictive and 536 opportunistic design data points. The DfAM tool survey collected 285 restrictive and 285 opportunistic design data points. The data was exported to MATLAB, where the data was encoded and sorted. This allows an output of average scores for each design, for both the non-tool and DfAM tool survey, which allows a direct comparison of the two data sets by mapping the output score of the DfAM survey to a 1-3 scale of the non-tool survey. The percent difference from the non-tool reported average and the DfAM output average was calculated, using Equation 2, for the expert class (starting with the restrictive designs).

$$R_n(\%\mathrm{DIF}) = 100 * \frac{\mathrm{Abs}\left(\mathrm{R}_{\mathrm{n}_{\mathrm{tool}}} - R_{n_{non-tool}}\right)}{\left(\mathrm{R}_{\mathrm{n}_{\mathrm{tool}}} + R_{n_{non-tool}}\right)/2} \tag{2}$$

Then, an average of all 12 percent differences was calculated to provide an overall comparison of experts evaluating them both with the tool and without. The mapping stage was then optimized for both the restrictive and opportunistic design sets to provide an expert-informed range for what makes a successful design in terms of restrictive and opportunistic DfAM. This results in the modified ranges as follows:

The following is presented for the restrictive section:

- 0-16% Major redesign required.
- 17-55% Some redesign required.
- 56-100% Will likely print with few issues.

The following is presented for the opportunistic section:

- 0-15% Consider other processes/adding features.
- 16-58% AM is a good candidate.
- 59-100% AM is a great candidate.

The initial interpretation of these scales contrasts the preliminary estimations on the current state of AM and the degree to which experts believe the quantity of restrictive or opportunistic elements are important. Our initial analysis provided a surprising result, that the experts within our study considered the opportunistic and restrictive elements to have essentially equal importance when evaluating a part for AM appropriateness. This contradicts our initial assumption that the current state of R-DfAM dominates and O-DfAM has a much lesser consideration in the design space. This may be due to a variety of reasons. Our initial prediction of the current climate may not have been accurate; a lack of research involving direct comparisons between these two restrictive and opportunistic spaces limits our understanding of the true way experts evaluate parts.

Next, to evaluate the accuracy of novice designers when compared to experts, the optimized maps were implemented into the analysis. The average score for each design was calculated for both the novice and expert classes. Firstly, the percentage difference was calculated between the control novice group (no tool) and the expert control group. Next, the percentage difference was calculated between the novices with-tool group and the expert with-tool group. These two percent differences were compared to determine if the introduction of the DfAM tool reduces the gap between novice and expert designers. The average values of these percent differences across the 12 restrictive and 12 opportunistic designs are shown in Table 6.

Table 6. Restrictive and Opportunistic % Differences between Novice & Experts.

	Restrictive		Opportunistic	
	Without Tool (Control)	With Tool (DfAM)	Without Tool (Control)	With Tool (DfAM)
Expert – Novice %Dif	10.3%	12.2%	15.7	3.99

Within the restrictive design set, a small increase in percent difference was observed with the introduction of the tool. A student's two-sample equal variance t-test was performed to determine the statistical significance of this percent difference. A non-significant difference between the absence and presence of the tool was found ($p = 0.583$, two-tailed). This indicates that there was no significant shift in the novice class towards the expert class when evaluating the series of restrictive designs. By contrast, within the opportunistic design set, a decrease in percentage difference was observed with the introduction of the tool. A student's two-sample equal variance t-test was run to determine the statistical significance of this percent difference. A statistically significant difference between the absence and presence of the tool was found ($p < 0.05$, two-tailed). This indicates that there was a significant improvement in novice designer ratings of opportunistic designs when compared to experts with the introduction of the tool.

The reason for this discrepancy leads the way for future research. However, an initial analysis into the questions themselves may indicate a preliminary area of interest and potential for the future development of such a tool. Figure 12 plots the percentage differences between novices and experts, separating each question. The plot divides the restrictive and opportunistic questions. As shown, questions two, four and five present higher variations when compared against the other questions. These questions specifically ask about overhangs, self-supporting angles, and sharp corner intensity, respectively. One potential reasoning behind this is that there may be an overlap in how the novice designers interpreted some of the more complex geometry categorizations. When evaluating the overall difference between both sections, it is possible that novice designers may find it easier to interpret and spot the presence of more obvious opportunistic features, such as lattice structures, embedded components, or multi-material prints than potentially more nuanced restrictive elements.

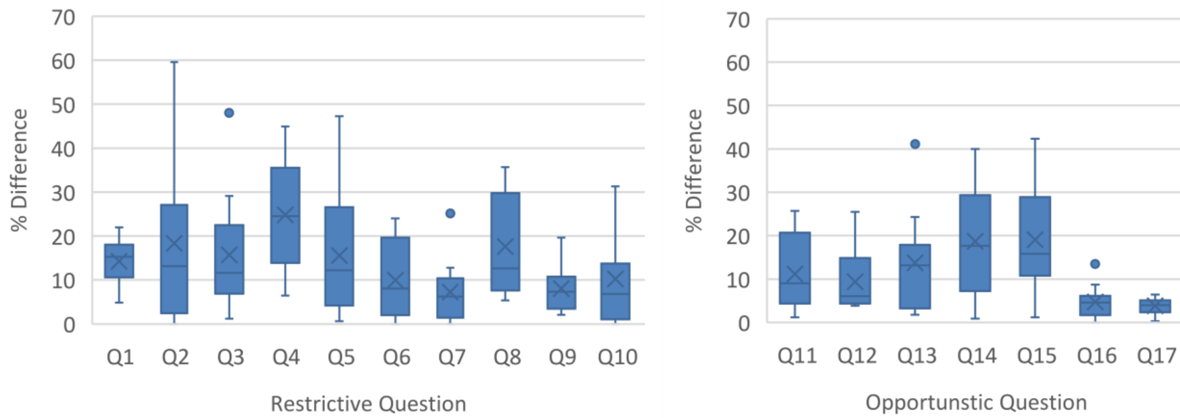

Figure 12. Question variation in novice-expert percent difference

Lastly, the same class groups were compared to evaluate the percent difference in design ratings when introducing the design tool. Here, the expectation is that the percent difference for experts will be lower than novices, as the tool should be representative of expert analysis without using the tool. Table 7 presents the percentages for both restrictive and opportunistic design sets. As shown, the results presented confirm our expected results, with experts in both restrictive and opportunistic sides presenting an average lower percent difference than novices.

Table 7. Restrictive and Opportunistic % Differences between Novice & Experts.

Restrictive		Opportunistic	
Novice-Novice % Dif	Expert-Expert % Dif	Novice-Novice % Dif	Expert-Expert % Dif
21.1%	10.4%	13.1%	8.88%

5. CONCLUSIONS AND FUTURE WORK

The framework presented in this paper built upon the functionality of previous approaches in producing a DfAM tool. As explored through the literature, there are several key studies examining the foundational approaches necessary to better suit the design process for AM, and previous tools have utilized some of these approaches, but none have fully integrated several key elements. Dual DfAM was implemented into this tool due to the growing research in exploring its impact on the design process, and conclusive evidence to assert it outputs more useful, unique, and technically good designs. A preliminary study showed that AM experts score the importance of various features differently across their own domain and that there is variation in scores for specific design features across different processes. Therefore, the inclusion of a novel weighting system was presented and showcased with a preliminary set of data, which is used in the end-user R-DfAM score. Additionally, this data was utilized to internally score processes at each stage and output a ranked list of processes which builds on the evaluation that different processes have different technical limitations or benefits. A user study evaluated both the restrictive and opportunistic sections and found that at this time, there is not a statistically significant change in novice design evaluation when compared to experts using the restrictive side. However, the study shows that the opportunistic side was able to significantly bring novices up to the expert level when evaluating if parts *should* be printed. Additionally, the output percentages were able to be categorized by comparing self-evaluations from experts with expert outputs from the DfAM tool. This presents a method for future work and a preliminary quantification of the current state of both opportunistic and restrictive DfAM.

While the initial study indicated that such a design evaluation tool can be effective in bridging the gap between novice and expert designers when evaluating designs for AM, it is crucial to continue the work, specifically on the restrictive side. A greater sample size should be obtained for experts, which is crucial as this group drives the entire functionality and categorization of design evaluation outputs. Furthermore, various question languages/content could be implemented to verify what language and questions should be implemented to reduce ambiguity and variation across novice users, particularly on the restrictive front. Overall, a greater sample set of both experts and novices should be utilized to maximize the data points. Because the surveys collected information from 24 designs, the end data points were relatively limited. Furthermore, both experts and novices were concentrated in a Northeastern US university, further work should be done to collect a broader range of respondents. As stated throughout the paper, the need for such a design evaluation tool is growing. The fundamental approach to designing a part is in strong contrast to how parts are traditionally designed. Not only are the core concepts of dual-DfAM important for novice designers to grasp, but the fundamental design philosophy when using AM shifts the status quo to how parts are designed. DfAM is centered around design freedom, optimization of performance and functionality, and the ability to quickly iterate and produce complex parts with minimal material waste. These concepts are critical to STEM based curricula which incorporate AM or DfAM, and providing a design evaluation tool that effectively captures this new design landscape will help the designers of the future fully leverage this technology and produce innovative designs.

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