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TOWARD A COMPREHENSIVE FRAMEWORK FOR PRELIMINARY DESIGN EVALUATION IN 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. The 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 demonstrates the potential of the framework through a series of case studies geometries. 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 and the approaches are not yet fully developed [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.

Following this 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].

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 tool 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, they offer a piecemeal approach to design evaluation, often limited in the DfAM rules that they consider or 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 percentage of successful and meaningful prints should increase. However, the work presented includes limitations due to a lack of thorough user-testing and expert analysis. Due to the novelty of several AM technologies, only six processes were considered for the tool. Furthermore, the tool only considers design principles that were found to be the most abundant within existing literature, certain specific or arising issues may not be represented in the tool. Lastly, the empirical merit of this initial study is limited due to a lack of data, which is required for future development.

2. LITERATURE REVIEW

DfAM 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 [11]. 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 [12]. 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. [13] 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 [14]. 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 [15]. 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 [15,16] 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 [18]. 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 [19], 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 [20].

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. Despite the significance for innovation, dual DfAM methods only account for approximately 30% of existing DfAM methods in research [13]. 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) [21]. 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 [22] 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 have been tools presented to cater towards the opportunistic side. As an example, design heuristics cards have been used to educate designers on how to take advantage of O-DfAM to improve their designs [23]. 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 have been found to 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 [24] 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 assistant in innovative ideation. Additional studies showed the effectiveness of these cards in producing significantly improving the novelty and quality of ideas [25].

Computational and automated tools have also been presented to cater to this growing need of early stage design evaluation for AM. Kumke [14] 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. Many emerging frameworks aim to provide process recommendations to the users, but require post-design knowledge such as production quantity [26], material cost [27] or surface roughness [27], [28] 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.

3. RESEARCH OBJECTIVES

While tools to assist novices in evaluating a design's adherence to DfAM are growing in number, there are still significant opportunities to propose a more comprehensive framework capable of capturing the breadth of dual DfAM, as well as the range of available AM process types. As discussed in the literature, existing tools for early-stage design evaluation in AM are limited in several key areas:

- Most tools focus only on the restrictive or opportunistic side, not implementing a dual-DfAM approach.
- Previous restrictive evaluation tools lack detailed visuals to adequately communicate certain features to novice AM designers.
- Previous worksheets assume every DfAM consideration is of equal importance in ensuring print success rather than implementing a weighting system.
- Previous worksheets focus on numerical feedback in the form of a scoring category. This may not provide the user with sufficient details or feedback what to redesign or why their design may not be appropriate for AM.
- More comprehensive DfAM analysis tools tend to be complex and lack a simple, holistic analysis aimed towards novice designers.

Considering this existing state-of-the-art, the purpose of this paper is to present a framework suitable for use in a tool that suggests the suitability of AM to a user for a specific design. The framework accounts for both opportunistic and restrictive design elements to capture a holistic view of the design input. Additionally, the paper presents a method for considering the range of available process types, to help guide a user to appropriate AM processes for their specific design. After presenting the specific structure for each part of the framework (Section 4), its potential will be demonstrated through a series of case studies (Section 5) to confirm the expected output and demonstrate the usefulness of the framework in different design evaluation scenarios.

4. STRUCTURE OF THE PROPOSED FRAMEWORK

This paper presents a solution for a framework that builds upon prior research and improves upon the previous points in Section 3. Specifically, this proposed framework aims to develop the following features:

- Implement both restrictive and opportunistic elements to utilize a Dual-DfAM approach for a more holistic evaluation of if AM is an appropriate approach.

- Implement a weighting system that more accurately evaluates the importance of each design element rather than assuming each element is of equal importance.
- 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.
- Implement a set of questions that relate to elements using process-agnostic language to ensure the tool has a wider usability.
- 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.
- Increasing the user engagement and detail of the tool by providing detailed and clear visual aids (including digital 3D manipulables) that accompany each question.
- Generate a series of detailed redesign recommendations based on user input to provide score transparency and informative outputs.
- 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.

The high-level structure of the framework is shown in Figure 1. It outlines the major segments of the framework that enables an input design to be evaluated and scored.

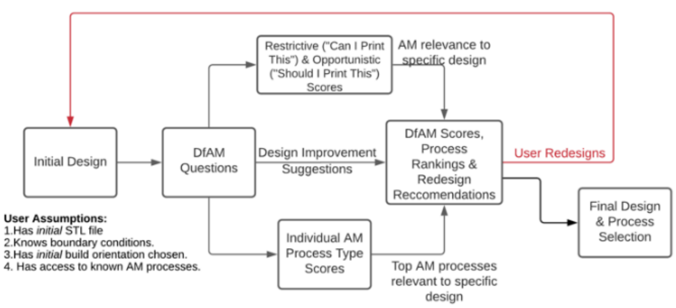


FIGURE 1: OVERALL FRAMEWORK FLOW

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 (Section 4.1/4.2) are evaluated in the framework via an R-DfAM question set and then an O-DfAM question set (Section 4.3). 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 (Section 4.5). 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 that 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 (Section 4.4), specific processes are ranked and recommended to the user for their design. Final recommendations compiled and output to through in a digital format (Section 4.6). 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 provides additional detail to support its relevance to the proposed framework.

4.1 Inclusion of Dual-DfAM

Laverne's study [13] 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 [21] 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 both if a part *can* be printed (R-DfAM) and if a part *should* be printed (O-DfAM) in a dual-DfAM approach.

Several worksheets focus on the restrictive side while design heuristics focus on the opportunistic side. 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 (such as a simple geometry which could otherwise be machined using TM). To account for the needs of both R-DfAM and O-DfAM, the proposed framework includes evaluation questions related to the 17 dual-DfAM considerations presented in Table 1.

TABLE 1: 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 1 were selected through consideration of previous R-DfAM and O-DfAM tools presented throughout this paper. Common overlaps were identified between various tools in the literature and presented. Only elements which were functionality-independent were chosen to provide a feature-based approach.

4.2 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 have been demonstrated in prior DfAM research. Zhang [29] 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 [30] 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. While the tool lacks user or expert validation, it was successful in accurately analyzing build time estimations utilizing its feature-based approach when compared to standardized build time estimation tools. Additionally, Maidin [31] presented a series of experiments in which AM novices utilized a DfAM feature database and the results "provide evidence that the AM feature database has been inspirational, useful, relevant and helpful to support the conceptual design of parts and products."

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. The tool only assumes the user knows initial boundary conditions and the print orientation of the part.

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. For example, the previously presented worksheets have sections on part functionality or tolerances which impact the decision-making process. It is important to realize the impact that end use case may impact the design process itself and the applicability to AM.

4.3 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. This adds consistency between elements. Owing to those previous approaches, and other use of scales in similar tools [22], this tool maintains a similar structure for the questions which provides sufficient resolution for early-stage design. Additionally, research [30, 31] has shown that a 3-point Likert scale is sufficient in meeting criteria of test-retest reliability which enables adequate consistency across users. 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. An example of a question presented to the user is 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. For example, rather than using numerical values in Figure 2, general terms such as *long* or *short* are used in cases where exact values can vary considerably across processes. 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. Figure 3 shows one question in which it was determined that minimum feature size has sufficient consistency across processes [16, 34–38]

Small Features

Q7: Does your part contain any small geometric features?

a. My part has geometric features less than 1mm.
b. My part has geometric features between 1-2mm.
c. My part has geometric features greater than 2mm.

FIGURE 3: RESTRICTIVE QUESTION EXAMPLE WITH VALUES

The opportunistic questions follow a similar format (Figure 4) 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. However, the language used does incorporate leading descriptions that communicate with the user the importance and relevance of certain elements. Figure 4 contextualizes the usage of lattice structures by introducing the concept of geometric complexity. This language not only provides relevance to the question but guides the user in the DfAM process. The language and relevance of these questions were obtained from previous approaches to this tool. Certain opportunistic elements will prevent the use of specific processes, which will be outlined in Section 4.5.2, but the questions themselves utilize language which does not focus on specific processes.

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 4: OPPORTUNISTIC QUESTION EXAMPLE

4.4 Visuals

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. 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.

This approach 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. Dale [39] quantified that written (reading) learning led to 72% and 10% information retention rates after 3 hours and 3 days respectively whereas visual aids led to 85% and 65% retention rates respectively. Presentation modalities for heuristics have been explored and research [40] has explored how users perceive heuristics with text-only, text with illustration, text with industry example, and text with 3D printed examples. Users rated the text-only approach as being the most difficult to understand concepts, with the latter three having no significant differences in user interpretation. When provided with this tool, 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 5, the framework presents the user with realistic, rendered 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. For example, in Figure 5, each varying degree of overhang corresponds to a matching render. These models were generated internally by DfAM domain researchers to represent an idea of the final application. While the images are generic to each user, they provide the user with a clear and concise representation of the element to reduce ambiguity and allows for the user to interpret each element quicker.

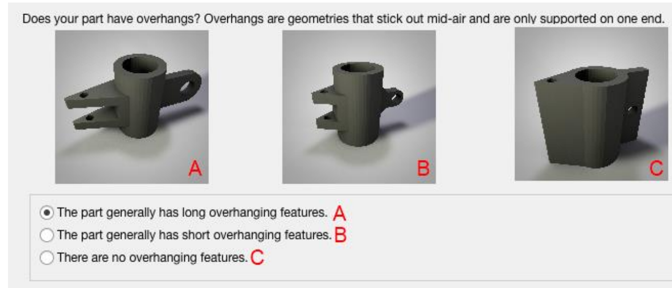


FIGURE 5: VISUAL AID EXAMPLE

In addition to static images, the framework includes the use of 3D STL models that physically represent the same models presented in the static image, as shown in Figure 6. This added layer of interactivity presents additional information to the user and may create a more engaging tool. Alvarez [41] 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 [42] 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.

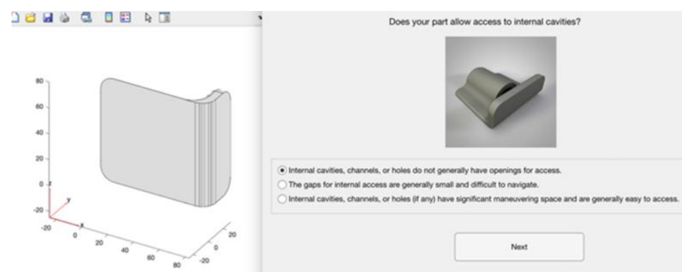


FIGURE 6: DFAM TOOL USER INTERFACE WITH 3D MODEL

This addition of both clear static imagery as well as interactive 3D models within the tool maximizes clarity. This not only increases the framework's reliability on an individual basis but will ideally produce a more uniform collection tool across multiple users for testing and final use.

4.5 Scoring

The scoring system that previous worksheets present assume that each DfAM element has equal importance 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

[16] whereas with most other processes support structures are required due to the method of deposition [43]. 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 [44]. 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 consisting of seven questions was internally distributed to a series of AM domain experts. They were asked to (1) self-identify as an expert of any number of AM process types of their choosing and (2) score each R-DfAM element from Table 1 on how importantly it would need to be considered within a design context to ensure a successful print. In the end, 26 responses were collected, representing six of the seven AM process types. Only sheet lamination was unrepresented; no respondents self-identified as experts in this process type, likely due it its niche position in the AM process landscape [39-41].

Figure 7 shows the expert survey, allowing each element to be independently scored for a specific process between 1 and 10, where 1 requires the least importance in design consideration and 10 requires the most importance in design consideration. To ensure all experts interpreted the considerations similarly, a more detailed explanation for each element was available when the respondents hovered their mouse over the element name. For example, Improving Internal Access had a description of "*Internal Access refers to ensuring cavities, channels or holes are accessible to remove potential support structures*." The survey also collects the years of experience for all respondents to confirm the cause of potential outliers when determining an average for each element for each process. In this case it was used to remove an outlier from material extrusion, where the respondent was found to have less than one year of experience with the technology.

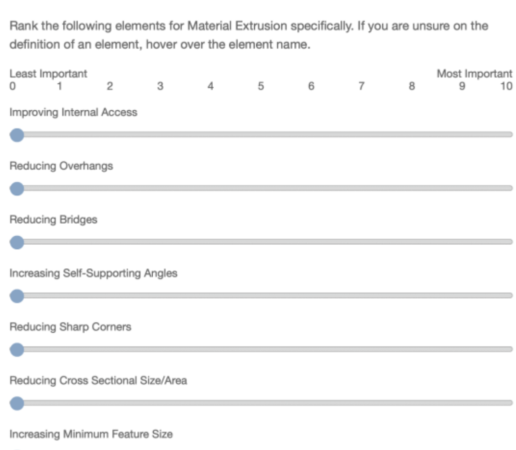


FIGURE 7: EXPERT SURVEY EXAMPLE

After collecting all expert responses, it enables a preliminary set of weights that represent the design consideration importance for each restrictive element within each process. To determine the overall AM restrictive weighting scale, each element is averaged across all processes. For the initial testing of this framework, the values shown in Table 2 are utilized for the restrictive scoring. As the table shows, there is variation across the AM landscape for various restrictive elements. Although these scores are preliminary and would require more data to accurately represent the elements, the initial values already further indicate variability across AM. As an example, the most highly weighted consideration *Improving Internal Access* is weighted 1.74 times higher than the lowest weighted consideration *Reducing Sharp Corners*. Considerations related to support structures generally tended to be weighted the most highly by experts across process types.

TABLE 2: 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

4.5.1 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 8. It outlines the tool's process at each question where the user's answer (*a, b, or c)* multiplies the overall restrictive score (Table 2) for that question and the individual process scores for that question, and continuously sums the scores throughout the restrictive section.

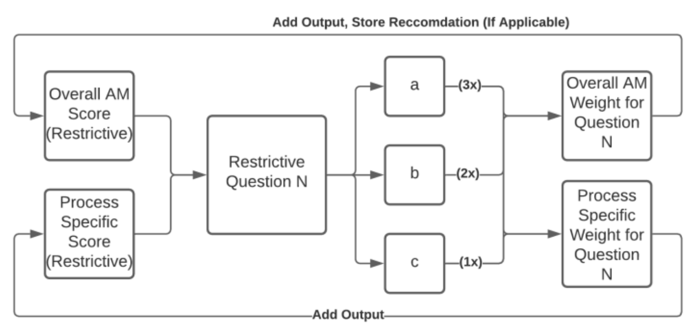


FIGURE 8: RESTRICTIVE FLOW

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 (examples shown in Table 2) for that specific question to produce a weighted answer score. For example, if the user selects *b* for *reducing overhangs,* that particular 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.

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

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.

4.5.2 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. Variations in score are due solely to the responses chosen by the user in each question. The reasoning behind the different approach for the opportunistic section is due to its importance being subjected to specific use cases when analyzing the importance of opportunistic elements for a specific design. Restrictive DfAM presents systematic guidelines, and the importance of each element can be estimated through literature or surveys as presented earlier in this section. However, opportunistic DfAM has no clear hierarchy of importance, because O-DfAM 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 9 displays the overall flow of the opportunistic section of the framework.

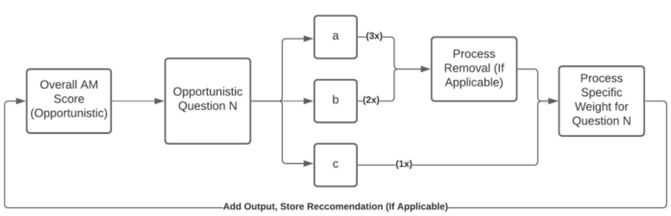


FIGURE 9: OPPORTUNISTIC FLOW

Though opportunistic 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 to O-DfAM, as outlined in the literature review. Literature was examined for each process to determine which of the opportunistic elements would not be technically possible or feasible using a specific AM process. If a user selects answer option *a* or *b* for either of the two questions, the listed process is completely removed from the ranking and will not be recommended to the user. Table 3 displays processes that are removed in this tool at specific questions, with references for each process. As an example, powder-based processes with highly controlled build environments are typically considered not to be viable candidates for embedding internal components. Likewise, not all process types have commercially viable systems capable of depositing multiple material phases within a single build.

TABLE 3: PROCESS REMOVALS DURING OPPORTUNISTIC ANALYSIS

	Multiple Materials	Embedded Internal Components
Processes Removed	VP [48] BJ [49] PBF [50]	PBF, DED [51]

4.5.3 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 previous worksheets, to help the user interpret the meaning of these percentages. As outlined in the literature, restrictive DfAM currently dominates the AM landscape, so the scale is set much lower for the opportunistic section:

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 [13]. We identified through a preliminary examination of available 3D models on websites such as MakerBot Thingiverse and GrabCad that designs with a score of 3 in more than two categories were among the highest available, and we would anticipate a design scoring a 3 in every category to be exceedingly rare. However, as DfAM evolves they would become more common and would require fine tuning of the scale to represent the standard design practices more accurately.

4.6 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 using the MATLAB GUI environment to create an app that incorporates the full functionality presented in this section, as shown in Figure 10.

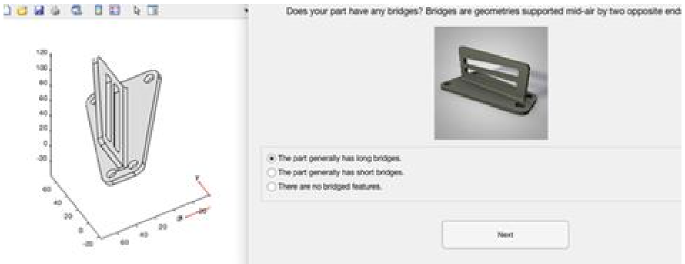


FIGURE 10: DFAM TOOL USER INTERFACE WITH 3D MODEL

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. Within a question, when the user selects an individual option (*a, b, or c)* the image within the interface as well as an interactive 3D model updates (as shown in Figure 10) to match the selected option. This added layer of interactivity with a digital tool can produce more positive learning motivation and more positive effects on learning outcome [52]. Additionally, studies [46, 47] have supported the claim that students exposed to interactive visual learning tools perceive the activity they are completing as more useful (utilitarian value) [54] and more enjoyable (hedonic value) [53] than their non-digital counterpart. 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 [55]. 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. The R-DfAM and O-DfAM scores and the process ranking system calculations can be performed in the back end, 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. A potential output is shown in Figure 11, in which the restrictive and opportunistic scores, process scores and redesign recommendations are shown.

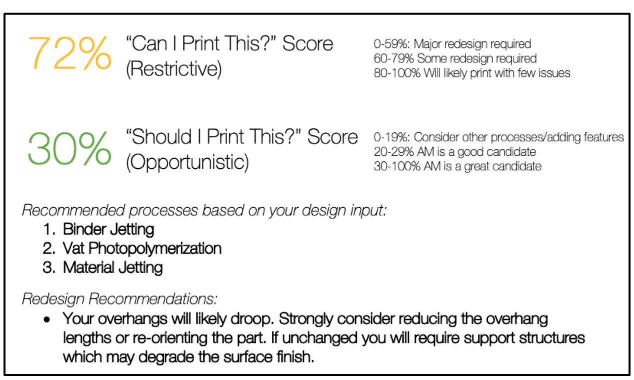
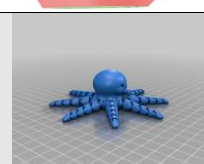
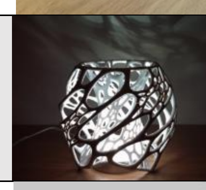


FIGURE 11: EXAMPLE OF POTENTIAL TOOL OUTPUT

5. CASE STUDY ANALYSIS

To test the variability in score outputs for the framework, several case studies were identified through online 3D CAD/model sharing websites. While it is important to understand that the tool is still in development due to the lack of a cohesive data set for process weights, the framework itself can be evaluated to determine the sensitivity of various design inputs and what the tool outputs. Various designs that exemplified either/both high and low qualities in restrictive and opportunistic DfAM were chosen to represent variation in potential design inputs and how the restrictive and opportunistic percentages reflect this variation. Table 4 presents 6 case studies that were selected to test the functionality of this tool, the designs were obtained from MakerBot Thingiverse and GrabCad.

TABLE 4: CASE STUDY SCORE OUTPUTS

Design	R-Score	O-Score	Process Ranks
	79%	29%	(1) BJ (2) BP (3) MJ
	84%	14%	(1) MJ (2) DED (3) ME
	90%	36%	(1) BJ (2) MJ (3) VP
	94%	0%	(1) BJ (2) VP (3) MJ
	68%	43%	(1) BJ (2) VP (3) MJ
	50%	0%	(1) BJ (2) VP (3) MJ

As shown in Table 4, there is variation between restrictive and opportunistic scores for each of the input designs. The resolution of the tool and inclusion of the weighting scale indicates that the response is more personalized than previous framework attempts due to the added detail in the output for a specific design input.

Additionally, the variation in process recommendations indicate additional personalization for the user and an output of applicable information for the individual design. It should be noted that these preliminary process weights would generally tend to favor Binder Jetting since it is ranked highly in every question. This is because Binder Jetting does not require support scaffolding material, it does not undergo thermal effects like distortion, shrinkage or cracks and has a fine print resolution [16]. Therefore, Binder Jetting outperforms other commercially available processes in these areas [44] so we would expect it to be rated highly regardless of the design input (with the exception of process eliminations).

The results shown in Table 4 simulate scenarios in which designs meet or miss the restrictive criteria, opportunistic criteria or meet or miss both criteria. With the included key on the tool's output and the generated re-design recommendations, this tool provides additional information compared to previous t tools. For example, when inputting the vise design into Booth's worksheet, it outputs a score of 15, which indicates a "Higher likelihood of success" for this vise. When considering R-Score solely, both tools provide similar outputs and provide the user with information on how likely the print will succeed. However, what previous tools lack is the additional information on *if* the user should be printing this. For the vise design in particular, it scores very highly for the R-Score but has a 0% score for the O-Score because it could easily be fabricated using a TM method, due to it not utilizing any benefits of AM. Additionally, when inputting the *Benchy* boat into previous tools, a similar R-Score would be expected but would not take into account the added utilization of AM through multi-material usage, which is accounted for through this presented framework.

6. CONCLUSIONS, LIMITATIONS, & 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 have been 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 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.

This research serves as a preliminary investigatory study into the design of a DfAM framework. To present a user-ready version, additional research is required to obtain data and validate the tool in user studies. Twenty-six responses were collected for the weighting implementation and some variation in responses were observed. Therefore, a much greater data set is required to validate both the claim to implement a weighting/ranking feature in such a tool and to validate the accuracy of the tool itself. Additionally, following the procedures of previous research, a design study would be undertaken to evaluate user experience, usability and perceived benefit of the tool as well as evaluating design improvements compared to control experiments when using the tool.

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