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EXPLORING THE MANIFESTATION OF DESIGN FOR MANUFACTURING AXIOMS IN STUDENTS' EARLY-STAGE ENGINEERING DESIGN CONCEPTS

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ABSTRACT

Additive Manufacturing (AM) is a technology capable of producing designs that challenge those from traditional manufacturing methods. AM is of high interest for advanced capabilities such as leveraging free complexity and having the ability to manufacture multi-part products that are manufactured as a single assembled. By leveraging design heuristics for AM, the final design can be manufactured in a shorter timeframe with less material consumption while still maintaining the initial engineering goals of the design. Despite the promising potential of AM, there is a growing concern that designers are not utilizing the design heuristics that embody successful AM. When designers resort to using design heuristics for Traditional Manufacturing (TM) with the unintentional purpose of translating these heuristics to AM, they are not creating efficient designs for AM and are unable to reap the benefits of using AM. To remedy this problem, intervening early in the design process can help address any concerns regarding the use of AM design heuristics. This work explores the design heuristics that students use in creating designs in the context of TM and AM. Once the common design heuristics students use in their designs are identified, future studies will further investigate the specific features that these students are using to address them through early interventions. This work found that incorporating complex shapes and geometries and considering the minimum feature size are significant axioms for influencing the manufacturability of a design for both TM and AM.

Keywords: Additive Manufacturing, Feature Analysis, Design Heuristics

1. INTRODUCTION

Additive Manufacturing (AM) is a still a relatively new method of producing designs. By utilizing the technology's approach to developing designs by adding material to an empty build volume, the wasted material that comes from the subtractive principles of Traditional Manufacturing (TM) are significantly mitigated. Additional benefits of AM over TM include its ability to produce far more complex designs [1] and its capability to directly assemble multiple parts together during the manufacturing process [2,3], thereby eliminating the time needed to assemble the product. AM has already demonstrated itself viable in applications ranging from prototypes [4] and end use products [5].

Manufacturing processes have associated design considerations that can help create a better design for a certain manufacturing process. Design for Manufacturing (DfM) provides the guidelines or heuristics for creating designs that leverage the chosen manufacturing process [6]. Relevant to this work, there are two sets of DfM heuristics that are highlighted: Design for Traditional Manufacturing (DfTM) and Design for Additive Manufacturing (DfAM). The key difference between these two sets of heuristics is that DfTM often favors simple designs, while DfAM favors those that are complex [1]. It is crucial to keep these sets of heuristics tied to their respective manufacturing process, as using the wrong set of heuristics for a different manufacturing process can lead to inefficient designs that don't take advantage of the selected process [7]. Because TM may likely be more familiar to designers due to its longevity compared to AM, these designers, who may be heavily influenced by their prior experience [8] may end up instinctively using DfTM heuristics in their designs, regardless of the manufacturing process they actually intend to use. For those looking to create designs for AM, this behavior is strongly discouraged and needs to be remedied. By leveraging the advantages that AM offers, such as the ability to produce pre-assembled products [9,10] and create replicas of scanned objects [11], designs that were previously impossible to manufacture using TM are now conceivable with AM because of the differences in limitations of each process [12].

One possible solution for addressing a designer's natural tendencies is to focus efforts early in the design process. It has been found in prior literature that the best opportunity to fix a design without wasted costs is the concept generation phase [13]. By addressing the usage of design heuristics in the concept generation stage, the designs can be better tailored to the chosen manufacturing process. Prior research has explored interventions in the concept generation phase [14], where specific focus has been given to the AM space [7,15,16]. Despite these efforts to investigate the ability to influence designers with DfAM heuristics, there is currently no in-depth analysis given to the heuristics that students instinctively use when they create designs. By understanding the heuristics that embody the designs that students produce, we can have a better understanding of the decision-making that takes place during the concept generation phase [17]. The purpose of this work is to identify the common heuristics that designers use in an effort towards building proper intervention methods.

2. LITERATURE REVIEW

To contextualize the research in this paper, it is important to understand the importance of DfM heuristics in concept generation (Section 2.1), and why it is necessary to focus efforts towards leveraging DfAM heuristics in this stage (Section 2.2).

2.1 The Importance of Design for Manufacturing Heuristics in Concept Generation

Design heuristics are a beneficial tool that can be used to describe an object. A design heuristic can be used to help designers identify features and flaws that manifest in designs [18]. One key aspect of design heuristics is that they are subjective in nature, which means they may be susceptible to influence from cognitive biases [19]. Despite this, design heuristics are still predominantly used in identifying the distinguishing characteristics of an object. Design heuristics have been used across a wide range of applications, including design evaluation [20], aiding in design development [21], and assisting in design education [22]. Design heuristics are of particular interest for the manufacturing assessment in this paper, as they have been previously used to classify designs based on their identified feature sets [23].

Design heuristics are also a critical aspect of the design process that can be implemented as guidelines for design considerations. Design heuristics act as cognitive principles that guide designers for interpreting designs and their potential variations [24]. Design heuristics have been recognized as valuable tools in the design process, both for providing guidance in design creation [21] and for use as an assessment tool for evaluating designs [20]. It is because of this significance that it is critical for design heuristics to be established early in the design process to ensure that the finished product embodies the proper principles.

Identifying relevant design heuristics early in the concept generation stage can help address any problems that may arise in the final product. By addressing problems early in the concept generation stage, it is easier to fix the designs and saves any potential wasted costs, as stated by Lough et al. [13]. In their work, they explore the benefits of design adjustment in the context of risk aversion, but they did not specifically explore the benefits of addressing the design to improve manufacturability. Yilmaz et al. [25] explored various intervention techniques in the concept generation stage, where it was found that interventions can influence the type of design thinking encouraged. Their results indicate that interventions are successful in getting designers to rethink their designs as they develop them in the concept generation stage. Part of these interventions involve determining which design heuristics should be presented, as there are many different types based on the relevant context.

2.2 The Differences in Heuristics for DfTM and DfAM

Design heuristics can be further isolated into different applications based on specific use cases. Relevant to this work, there are a set of heuristics for DfTM and a set for DfAM that are tailored for TM and AM, respectively. The design heuristics for traditional manufacturing have long been in place and introduce standard considerations for creating simple designs suitable for TM [26]. Newer DfAM heuristics narrow the breadth of design properties to those that are advantageous when AM is being used for production. DfAM heuristics were derived by Blösch-Paidosh and Shea [27] as they collected and analyzed the key functions and features of 275 AM artifacts. Through their creation of the DfAM heuristics, they allude to various DfAM concepts manifesting in designs, with no constraints put on how many heuristics may be present for any given design and the frequency with which these heuristics are identified relative to the total number of sampled artifacts. These design heuristics have been used across the engineering design process, ranging from design ideation [28] to design inspection [29,30] and redesigning [31,32]. These DfAM heuristics have useful applications within the design process and how it relates to AM, as evidenced in the review conducted by Valjak et al. [33].

Design heuristics for AM drastically differ from those geared towards TM. While designs for AM favor complexity, designs for TM prefer simplicity [1]. It is because of these differences that design considerations must be implemented early in the concept generation process to create designs that are best suited for one process over another. Designs can be inefficient or outright not be manufacturable when these design considerations (e.g., DfTM vs DfAM) are mixed and matched [12,34]. To reduce the chance of these considerations being mixed into one design, there is a need to address the differences between DfTM and DfAM early in the design process. One method for achieving this is to perform an intervention prior to or during the design process, as was found by Prabhu et al. [16] and by Schauer et al. [7].

While prior literature has explored intervening to improve designs for AM, they do not consider the specific heuristics that represent the design itself in the context of both AM and TM. Blösch-Paidosh and Shea presented their developed heuristics in the form of cards and objects in an effort to stimulate design thinking towards AM [32]. While their findings of presenting heuristics to these yielded increased usage of DfAM heuristics in their designs, the students were likely framed towards AM from the beginning of the experiment [35] as the activities leading up to the design task were narrowed to AM-related topics only. Similarly, Prabhu et al. [16] leveraged the DfAM heuristics that were derived from Laverne et al. [9]. These heuristics separate the principles of DfAM into two categories: Restrictive (R-DfAM) and Opportunistic (O-DfAM), which correspond to the limitations and capabilities of AM, respectively. While their research analyzed the manufacturability of the designs through AM, they do not account for the use of DfTM heuristics and how designs might be improved for AM. Sinha et al. [36] explored the comparison of designs for TM and AM while controlling for any prior formal training. While their work encourages the continuation of DfAM education based on the students' abilities to create more elegant designs, their assessment process for dissecting the designs did not reach the heuristic level. There is a lack of research focusing on the evaluation of designs through lens of the two sets of DfM heuristics when the students are not heavily skewed towards one manufacturing process over another; there is a need to investigate the specific heuristics that designers may naturally gravitate towards using in their designs. By understanding the DfTM and DfAM heuristics that students are leveraging in their designs, interventions can be used to help designers reframe their thinking and overcome any fixation they may have towards their initial concepts [37,38].

This work focuses on performing an in-depth assessment of designs for their manufacturability in the context of traditional manufacturing and additive manufacturing. Design heuristics are the foundational basis for an assessment analogous to this, but the process is both vague [33] and complex [23] for novel work such as this one. Therefore, there is a need to conduct an assessment using explicit criteria so that future studies can build on this work by integrating design heuristics into this manufacturability assessment. The alternative presented in this work utilizes axioms in place of heuristics. Axiomatic design leverages design axioms for which its principles are well defined and are undisputed [39,40]. The approach to utilizing axioms has shared commonalities with heuristics [41] and there are applications where they are interchangeable [42]. The similarities between these two sets of design principles make using design axioms in place of design heuristics sufficient for this work, as the assessment of designs for their manufacturability will be done using precise criteria.

3. RESEARCH OBJECTIVES

The objective of this paper is to determine whether the students' perceived assessment of their designs is accurate when compared to expert assessment. By identifying where students differ from experts in how they perceive DfM axioms in their designs, future interventions can address these differences so students can have a better understanding of the axioms present in their designs. Further, the work seeks to determine the axioms that significantly influence the manufacturability of a design. There is a need to understand the axioms that students are utilizing in their designs so future interventions can address these axioms to create improved designs for either traditional manufacturing or additive manufacturing. The following research questions are proposed:

(1) How does the students' self-assessment of axiom usage correlate to the expert's assessment?

We hypothesize that students having prior experience with manufacturing (either TM or AM) will report an accurate perception of the axioms used that are associated with their prior manufacturing experience relative to their actual use. In contrast, students with no prior manufacturing experience will inaccurately perceive and assess axioms in their designs compared to their actual used. When controlling for experience, those with higher experience have demonstrated in prior research to report more DfM axioms than those with lower experience [43]. Because DfAM is still in its relative infancy while having a niche audience [44], exposure to related axioms is expected to be limited. Therefore, by expressing high levels of expertise, it is anticipated that the students are aware of DfAM and can therefore provide a more accurate assessment of their designs when compared to the experts.

(2) To what extend will different DfM axioms predict the appropriateness of a design concept for TM or AM?

We hypothesize that students will inherently create designs that favor TM, where the design axioms that will significantly influence the manufacturability of the designs will be to avoid intricate shapes and to leverage low-labor-cost operations. Because students tend to create simple designs [45], it is anticipated that students will resort to designs that do not incorporate any form of shape complexity. Additionally, because these simple shapes can be treated with simple manufacturing steps [46], complex techniques will not be necessary.

4. EXPERIMENTAL METHODS

To answer the research questions, an experiment was developed to investigate the axioms used in students' generated designs. The experiment consisted of two stages: (1) a pre-intervention survey, and (2) a design challenge followed by students' self-evaluations of their designs. The study was reviewed and approved by the Institutional Review Board, and implied consent was obtained from the participants prior to the experimentation. In this experiment, the participants first reported their current level of expertise with TM and AM. Next, they were asked to complete an open-ended, manufacturing-agnostic design challenge. From there, they completed the experiment by self-evaluating their designs for TM and AM based on the axioms presented in the pre-intervention survey. Finally, after the design activity, participants' designs were evaluated by manufacturing domain experts. The following subsections discuss further details behind experimentation and analysis.

2.2 Participants

116 participants were recruited from a third-year undergraduate mechanical engineering design course. Some participants' data (not included in this numerical total) were removed from consideration due to incompleteness in the activity where key information was critical (i.e., the self-reported evaluation for the design considering the manufacturing size) or the key information was not filled in properly (I.e., the self-reported evaluation for avoiding large, flat regions had two scores filled in when only one was requested). The experiment was implemented during the middle of the Fall 2022 semester to allow students to gain manufacturing experience in their class prior to the experiment's design challenge.

2.2 Procedure and Metrics

2.2.2 ***Pre-Intervention Survey***

At the outset of the activity, participants were given 5 minutes to complete a survey that asked about their previous experience with TM and AM. They were also asked to evaluate their familiarity with a series of 14 different DfTM and DfAM axioms (7 for each) on a 5-point Likert-type scale [47], with a score of 1 representing "Never heard about it" and a score of 5 representing "Could regularly integrate it with my design process." This survey, which was modified from the studies done by Prabhu et al. [48–50], provides the research team with an understanding of participants' current levels of TM and AM experience and familiarity with the respective DfM axioms. The DfTM axioms were extracted from Bralla [26], while the DfAM axioms were extracted from Prabhu et al. [51]. A list of the axioms used in this experiment are presented in Table 1.

Table 1. DfM Axioms

DfTM Axiom	DfAM Axiom
Simplify designs to reduce part count without greatly increasing manufacturing complexity	Incorporate complex shapes and geometries to reduce material usage
Rely on low-labor-cost operations that minimize human manufacturing steps	Combine what might typically be multiple parts into a single product or assembly
Avoid intricate shapes that require multiple manufacturing operations or repositioning	Avoid large, flat regions that may be susceptible to distortion and warping
Leverage standard materials, components, and tooling for manufacturing	Orient overhanging surfaces to reduce the need for support material
Avoid sharp corners; use fillets to improve manufactured accuracy and reduce stresses	Consider the minimum feature size that can be resolved by the manufacturing process
Maintain a uniform wall thickness throughout individual parts	Orient curved surfaces to reduce surface roughness and increase part accuracy
Provide ample spacing between holes so they can be made without tooling weakness	Account for potential variations in material properties in different directions

2.2.2 ***Design Challenge and Procedure***

Following the survey, students were given the design prompt that they would be solving. The provided design prompt was as follows. ""You are tasked with designing a solution to hold three hollow tubes securely in place and parallel to each other. All tubes must be held 2 inches away from a fixed wall (measuring from the wall to the closest edge of the tubes). The tubes are 1 inch in diameter and 3 inches long"" To accompany this text description, participants were also presented with the visuals seen in Figure 1. This design challenge was previously used by Prabhu et al. [52] and Pearl et al. [50], was selected for this study because its open-ended nature creates a wide design space [52], allowing for solutions that can be produced using both TM and AM. Additionally, the design challenge falls in line with the shift towards problem-based learning [53]. To remove any manufacturing biases in the design challenge, students did not receive any manufacturing constraints in the design prompt itself. Furthermore, to understand how students would naturally create designs and evaluate them for their axiom manifestation, the students were not primed on any DfM concepts. The work from Pearl et al. [50], which has a similar experimental procedure to this work, had the students primed with DfTM and DfAM concepts before proceeding with the design challenge. By omitting the priming element of the procedure, the students have no exposure to understanding what each axiom entails, meaning their ability to create and evaluate their designs will be based primarily on their prior experience.

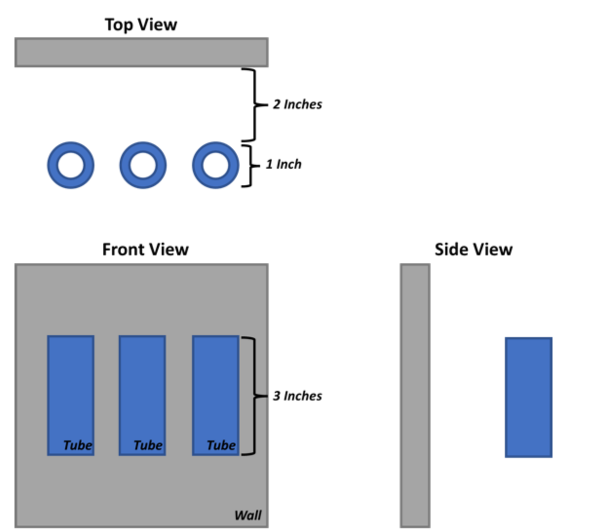

Figure 1. Design Challenge Visual Provided to Participants

After reading through the design challenge prompt, students spent 10 minutes using the provided design sheets to individually create as many solutions as possible. They were instructed to use both sketches as well as text to illustrate their designed solutions. While the students were creating designs in the concept generation session, they were also asked to describe the advantages and disadvantages of each design concept. An example of a completed design sheet is shown in Figure 2.

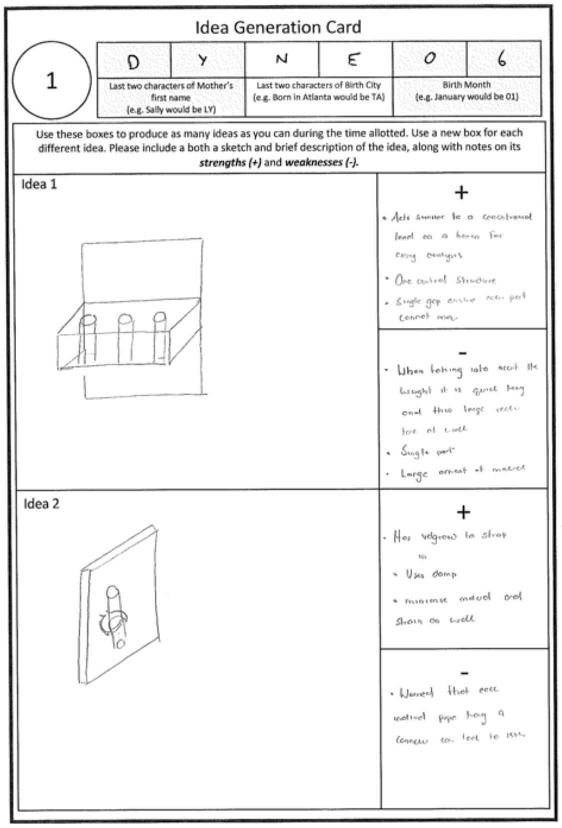

Figure 2. Example of Completed Design Sheet

Following the concept generation session, participants were given 7 minutes to identify a final design. They were informed that their final design could be any of the following: a reused or modified design from the initial concept generation period, a combination of any of the previous designs, or an entirely new idea. As with the initial concept generation session, participants were asked to list the advantages and disadvantages of their final design.

After identifying their final design and discussing its strengths and weaknesses, participants were asked to evaluate their solution as designed based on the 7 DFTM axioms and 7 DfAM axioms presented in the pre-intervention survey to the best of their ability. Specifically, participants were presented with each axiom and asked, “To what extent do you agree with the following statements about manufacturing as they apply to your final design?” They then evaluated the design using a 5-point Likert scale, where 1 represented Strongly Disagree and 5 represented Strongly Agree. This self-evaluation allows the researchers to observe which DfM axioms are commonly identified by the students and will be used to compare to the expert assessment, which is discussed in the following section.

4.2.3 Expert Design Evaluation

To evaluate participants’ final designs, three raters (two experts and one quasi-expert in design for manufacturing processes) used the Consensual Assessment Technique (CAT) as developed by Amabile [54]. This technique has expert judges evaluate creativity in their specialty domain [55]. Pertinent to the research in this paper, the CAT has also previously been used to evaluate suitability of design concepts for manufacturing [52,56]. Both expert raters have graduate degrees, have at least 6 years of experience with creating and evaluating designs for AM, and previously published papers in the relevant field. The quasi-expert is currently progressing through graduate coursework and has experience with creating and evaluating designs for AM. The three raters evaluated the final designs based on both their traditional manufacturability and additive manufacturability. Both categories were evaluated on a 1-6 scale, with higher scores indicating greater suitability for that manufacturing process type. A brief description of each category is as follows:

- <u>Traditional manufacturability:</u> The suitability of the design for TM based on expert assessment. Though a variety of traditional processes are possible, scoring is based on the assessment of applicable DfM principles. A higher score represents a design that utilizes the general principles of TM (simple shapes, rounded corners, ample spacing between holes, etc.) while a lower score represents a design that is either very difficult or impossible to manufacture using TM processes.
- <u>Additive manufacturability:</u> The suitability of the design for AM based on expert assessment. The category here focuses on the use of both R-DfAM and O-DfAM principles in the design and how they apply to the various AM processes. A higher score represents the use of most R-DfAM and O-DfAM principles, while a lower score represents little to no identifiable R-DfAM and O-DfAM principles. Intermediate scores tend to exhibit suitable R-DfAM, but lack in O-DfAM.

After evaluating the designs for their manufacturability, the raters proceeded to assess the designs for use of the 14 DfM axioms. The three raters first jointly scored 5 randomly selected designs together to establish the evaluation criteria and have general agreement. Next, each rater individually scored the same set of 25 randomly selected designs which were then compared for consistency. To calculate the inter-rater reliability, the scores were validated for consistency using the interclass coefficient (ICC) [57–59]. The ICC values were calculated using SPSS v.29. A secondary meeting was held among the raters to discuss any discrepancies, review the scores, and refine the rubric for assessing the designs after the initial ICC calculation yielded a poor Cronbach’s Alpha (α) for some of the DfM axioms. From there, an additional 40 designs were independently assessed, and the cumulative scores were compared for agreement. The manufacturability scores maintained a strong agreement, while the axioms ranged from moderate to strong agreement. The raters were then asked to evaluate the remaining designs and a final reliability test was performed. The inter-rater reliability results are shown in Table 2.

Table 2 presents α values that range from moderate reliability ($0.50<\alpha<0.75$) to good reliability ($0.75<\alpha<0.90$) [60]. These α values were also significant with a p-value of <0.001 using a 95% confidence interval. This means that for each design the raters were giving comparable scores for their manufacturability and usage of DfM axioms. This indicates a good agreement between the raters for all experimental conditions. After the raters evaluated all the designs, the average TM CAT score and average AM CAT score were calculated for each student by averaging the respective CAT scores provided by the raters. This process was also repeated for the DfM axioms. The resulting average expert rater is associated with 2 manufacturability scores (TM and AM) and 14 DfM axioms (7 DfTM and 7 DfAM) for 116 participants.

Table 2. ICC Results for the Three Raters

Evaluation Criteria	Cronbach's Alpha (α)
Traditional Manufacturability	0.771
Additive Manufacturability	0.828
Reduce Part Count	0.834
Rely on Low-Labor-Cost Operations	0.723
Avoid Intricate Shapes	0.740
Leverage Standard Materials, Components, and Tooling	0.715
Avoid Sharp Corners by Using Fillets	0.842
Maintain a Uniform Wall Thickness	0.769
Provide Ample Spacing Between Holes	0.713
Incorporate Complex Shapes and Geometries	0.858
Combine Multiple Parts into a Single Part or Assembly	0.847
Avoid Large, Flat Regions	0.848
Orient Overhanging Surfaces	0.769
Consider the Minimum Feature Size	0.793
Orienting Curved Surfaces	0.755
Account for Potential Variations in Material Properties	0.694

5. RESULTS

To communicate data collected through this study, this section details the distribution of students' manufacturing experience (Section 5.1), followed by statistical analysis using SPSS v.29 to answer the research questions for self-reported assessment against expert assessment (Section 5.2) and presenting a model for manufacturability (Section 5.3).

5.1 Experience Distribution

Before a concise comparison can be made between the students' self-reported assessment and the expert-evaluated scores, it is necessary to classify the students based on their experience level. To do this, the students' designs were categorized into groups based on the 5 available TM experience levels and the 5 available AM experience levels, resulting in 10 manufacturing experience groups. A breakdown of the number of students in each group is shown in Table 3.

Table 3. Participant Breakdown

Experience Level	Number of Students with TM Experience	Number of Students with AM Experience
1	14	7
2	51	55
3	33	38
4	16	11
5	2	5
Total	116	116

Within these groups, the students' self-reported scores were compared for general agreement by calculating the inter-rater-reliability. ICC values were calculated for the students' self-reported assessments using SPSS v.29. where all but one group yielded moderate reliability (the lone exception being the AM experience level of 4). With general agreement observed in each manufacturing experience group, the students' self-reported scores for each axiom within the groups were averaged out. This process gives us 10 average students (5 with TM experience at levels 1-5 and 5 with AM experience at levels 1-5), with each individual average student having 14 DfM axiom scores associated with them.

5.2 Self-Reported Scores Against Expert Assessment

To answer the first research question, a series of Paired T-Tests were performed comparing the 10 average students to the average expert rater. This test was chosen because we wanted to compare the average of two related groups (the self-reported scores against the expert scores across each manufacturing experience level) to determine if there is a significant difference between the groups [61]. For both groups, the assumptions of normality were met and no outliers were detected as assessed from the histograms [62] generated in SPSS v.29. With the 10 student containers previously defined, 10 new containers were created for the expert-assessed data. The process for categorizing and averaging the data was identical to the students' self-reported data, but now the average of the expert raters' scores for all individual designs is used. With 10 generated average students (5 students with TM experience ranging from 1-5 and 5 students with AM experience ranging from 1-5) and 10 generated average experts (5 experts linked to evaluate the designs from the 5 students with TM experience ranging from 1-5 and 5 experts linked to evaluate the designs from the 5 students with AM experience ranging from 1-5) 10 Paired T-Tests were performed, with the results shown in Table 4.

Table 4. Paired T-Test Results for Self-Reported Versus Expert Assessment

Student Container	Expert Container	T-Test Statistic	Two-Tailed P-Value	Cohen's d
TM Experience Level 1 (TM1)	Evaluation for TM1	1.524	0.151	0.407
TM Experience Level 2 (TM2)	Evaluation for TM2	2.833	0.014**	0.757
TM Experience Level 3 (TM3)	Evaluation for TM3	3.347	0.005**	0.894
TM Experience Level 4 (TM4)	Evaluation for TM4	3.524	0.004**	0.942
TM Experience Level 5 (TM5)	Evaluation for TM5	4.628	<0.001**	1.237
AM Experience Level 1 (AM1)	Evaluation for AM1	-0.745	0.470	-0.199
AM Experience Level 2 (AM2)	Evaluation for AM2	2.844	0.014**	0.760
AM Experience Level 3 (AM3)	Evaluation for AM3	3.936	0.002**	1.052
AM Experience Level 4 (AM4)	Evaluation for AM4	2.001	0.067*	0.535
AM Experience Level 5 (AM5)	Evaluation for AM5	5.723	<0.001**	1.529

*:p<0.1 **:p<0.05

As Table 4 shows, the only non-significant pairings between the students and raters were at the TM experience level of 1 and the AM experience level of 1. This means that for all other cases, the students evaluated their designs differently than the experts. Furthermore, the T-Test Statistic is positive in all but one instance (the pairing involving students with an additive manufacturing experience level of 1). This means for the majority of pairwise comparisons, the students overestimated their usage of DfM axioms in their designs compared to the expert assessment. Most of the Cohen's d values presented in Table 4 are of at least moderate correlation [63], indicating a large practical effect observed between the students and experts.

To understand which axioms the students and expert raters differed, additional Paired T-Tests were performed. Here, the average of the expert's scores were compared against all the students' scores in each of the 10 containers. The significant differences between the students and experts' scores are shown in Table 5 (the non-significant differences in assessments were omitted). The results in Table 5 show that except for the axiom "Account for Potential Variations in Material Properties" (which did not have any significant differences in assessment) and the five instances where the students assigned lower scores for their perceptions of DfM axioms in their designs compared to the expert assessment (these instances are indicated with a negative T-Test Statistic in Table 5), the students were assigned higher scores for their perceptions of DfM axioms in their designs compared to the expert assessment. Additionally, there were 7 axioms where at least 5 of the 10 manufacturing experience groups significantly differed from the experts: (1) Reduce Part Count, (2) Leverage Standard Materials, Components, and Tooling, (3) Avoid Sharp Corners and Use Fillets, (4) Maintain a Uniform Wall Thickness, (5) Provide Ample Spacing Between Holes, (6) Incorporate Complex Shapes and Geometries, and (7) Combine Multiple Parts into a Single Product or Assembly. Further expanding on these findings, we observe that 5 of these axioms are for TM, while 2 of these axioms are for AM. Additionally, most of the Cohen's d values presented in Table 5 are of at least strong correlation [63], indicating a large practical effect observed between the students and experts.

5.3 A Model for Predicting Manufacturability Based on DfM Axioms

To answer the second research question, a stepwise multiple linear regression was performed. This test was chosen because unlike forward or backward regression, stepwise both adds and removes predictor variables as necessary to get a resulting model [64]. The objective of the linear regression model was to predict the average of the expert-assessed traditional manufacturability and additive manufacturability based on the average of the expert-assessed DfM axiom scores. To equate the manufacturability scales (1-6) to the DfM axiom scales (1-5) both scales were normalized from 0 to 1, which was made possible by the lack of outliers detected [65]. The models generated from SPSS v.29 to predict traditional manufacturability and additive manufacturability are shown in Tables 6a and 6b, respectively.

Table 5. Axiom Differences between Students and Experts

Axiom	Manufacturing Experience Level	T-Test Statistic	Two-Tailed P-Value	Cohen's d
Reduce Part Count	TM2	3.523	0.001**	1.352
	TM3	4.045	0.000**	1.807
	TM4	2.959	0.010**	1.436
	AM2	3.537	0.001**	1.487
	AM3	5.985	0.000**	1.464
	AM5	2.828	0.047**	1.581
Low-Labor-Cost Operations	TM3	3.376	0.002**	1.341
	AM2	2.106	0.040**	1.537
	AM3	2.488	0.017**	1.370
	AM5	2.449	0.070*	1.095
Avoid Intricate Shapes	TM3	1.844	0.074*	1.416
	AM3	2.811	0.008**	1.558
	AM5	2.449	0.070*	0.548
Leverage Standard Materials, Components, and Tooling	TM2	5.953	0.000**	1.294
	TM3	2.635	0.013**	1.321
	TM4	3.873	0.002**	1.291
	AM2	4.886	0.000**	1.297
	AM3	4.762	0.000**	1.294
	AM4	2.319	0.043**	1.300
	AM5	2.746	0.052*	1.140
Avoid Sharp Corners and Use Fillets	TM2	5.708	0.000**	1.447
	TM3	5.013	0.000**	1.042
	TM4	3.529	0.003**	1.063
	AM2	6.708	0.000**	1.206
	AM3	4.755	0.000**	1.194
	AM4	2.609	0.026**	1.618
Maintain a Uniform Wall Thickness	TM2	2.517	0.015**	1.391
	TM3	3.802	0.001**	1.236
	TM4	4.226	0.001**	1.183
	AM2	3.296	0.002**	1.432
	AM3	4.338	0.000**	1.234
	AM4	1.896	0.087*	1.272
	AM5	2.746	0.052*	1.140
Provide Ample Spacing Between Holes	TM2	3.915	0.000**	1.180
	TM3	5.164	0.000**	1.011
	AM2	4.579	0.000**	1.090
	AM3	3.058	0.004**	1.220
	AM4	2.055	0.067*	1.027
Incorporate Complex Shapes and Geometries	TM2	4.860	0.000**	1.239
	TM3	2.517	0.017**	1.591
	TM4	3.578	0.003**	1.328
	AM2	3.662	0.001**	1.436
	AM3	3.612	0.001**	1.392
	AM4	3.786	0.004**	1.433
Combine Multiple Parts into a Single Product or Assembly	TM2	1.685	0.098*	1.662
	TM3	4.608	0.000**	1.587
	AM2	2.397	0.020**	1.631
	AM3	3.468	0.001**	1.590
	AM5	3.138	0.035**	1.140
Avoid Large, Flat Regions	TM3	-3.376	0.002**	1.341
	AM2	-1.932	0.059*	1.675
	AM3	-4.120	0.000**	1.063
Orient Overhanging Surfaces	AM5	2.138	0.099*	0.837
Consider the Minimum Feature Size	AM4	2.390	0.038**	1.514
	AM5	2.250	0.088*	1.789
Orient Curved Surfaces	AM2	-2.122	0.038**	1.462
	AM3	1.850	0.072*	1.841
	AM4	-2.043	0.068*	1.328

*:p<0.1 **:p<0.05

Table 6a. Traditional Manufacturability Model

DfM Axiom	Coefficient	T-Test Statistic	P-Value	Pearson R
Constant Term in Regression Model	0.243	2.884	0.005**	-
Avoid Intricate Shapes	0.189	2.176	0.032**	0.683
Rely on Low-Labor-Cost Operations	0.271	3.564	<0.001**	0.590
Leverage Standard Materials, Components, and Tooling	0.174	2.883	0.005**	0.266
Incorporate Complex Shapes and Geometries	-0.219	-2.778	0.006**	-0.661
Consider the Minimum Feature Size	0.121	2.181	0.031**	0.320

**:p<0.05 R=0.776 R^2=0.602

Table 6b. Additive Manufacturability Model

DfM Axiom	Coefficient	T-Test Statistic	P-Value	Pearson R
Constant Term in Regression Model	0.096	2.011	0.047**	-
Incorporate Complex Shapes and Geometries	0.490	9.954	<0.001**	0.622
Consider the Minimum Feature Size	0.206	4.065	<0.001**	0.193
Orient Overhanging Surfaces	0.118	2.174	0.032**	0.019

**:p<0.05 R=0.699 R^2=0.489

Tables 6a and 6b present the DfM axioms that can be used to predict the manufacturability of a design for TM and AM, respectively. The stepwise regression method, like other regression method techniques [64] can lead to predictors being removed from final model. This result is either due to certain predictors not having statistical significance or these predictors having a high correlation with one or more of the predictors in the final model (i.e., if predictors X and Y are highly correlated, knowing the manufacturability of a design based on predictor X leads to knowing the manufacturability of a design based on predictor Y). The justification for removing certain axioms from both models is not initially provided. This information is important to gather for this work because we need to understand which axioms were removed from the models yet have high correlation with the axioms present in the final models so they can be included in future interventions. While the data satisfied the assumption of non-multicollinearity (VIF<10 [66]), an in-depth exploration into the correlation values was performed to see which axioms had a moderate correlation (r>0.3 [67]). Table 7 presents all moderate positive/negative correlations (+/-) within the pairwise comparisons of axioms (note that strong correlations of r>0.5 are called out). The significantly correlated axioms that merit inclusion in interventions will be highlighted in the discussion section.

Table 7. Correlations Between Axioms

Axiom 1	Axiom 2	Pearson R Correlation	+/-	P-Value
Reduce Part Count	Rely on Low-Labor Cost Operations	0.488	+	0.000
Reduce Part Count	Leverage Standard Materials, Components, and Tooling	0.483	-	0.000
Reduce Part Count	Combine Multiple Parts into a Single Product or Assembly	0.754*	+	0.000
Reduce Part Count	Avoid Large, Flat Regions	0.310	-	0.000
Rely on Low-Labor Cost Operations	Avoid Intricate Shapes	0.606*	+	0.000
Rely on Low-Labor Cost Operations	Provide Ample Spacing Between Holes	0.365	+	0.000
Rely on Low-Labor Cost Operations	Incorporate Complex Shapes and Geometries	0.512*	-	0.000
Rely on Low-Labor Cost Operations	Avoid Large, Flat Regions	0.525*	-	0.000
Rely on Low-Labor Cost Operations	Consider the Minimum Feature Size	0.324	+	0.000
Rely on Low-Labor Cost Operations	Orient Curved Surfaces	0.367	+	0.000
Avoid Intricate Shapes	Orient Overhanging Surfaces	0.342	+	0.000
Avoid Intricate Shapes	Orient Curved Surfaces	0.380	+	0.000
Provide Ample Spacing Between Holes	Consider the Minimum Feature Size	0.373	+	0.000
Avoid Intricate Shapes	Incorporate Complex Shapes and Geometries	0.764*	-	0.000
Avoid Intricate Shapes	Avoid Large, Flat Regions	0.582*	-	0.000
Leverage Standard Materials, Components, and Tooling	Combine Multiple Parts into a Single Product or Assembly	0.569*	-	0.000
Incorporate Complex Shapes and Geometries	Avoid Large, Flat Regions	0.630*	+	0.000
Orient Overhanging Surfaces	Orient Curved Surfaces	0.481	+	0.000
Orient Curved Surfaces	Variations in Material Properties	0.313	-	0.000

*:r>0.5

6. DISCUSSION

Based on the experimental results, there are several key findings that merit more in-depth discussion

- Students perceive more DfM axioms present in their designs when compared to expert assessment.

- Incorporating complex shapes and geometries and considering the minimum feature size can significantly influence the manufacturability of a design.

6.1 Students perceive more design axioms present in their designs when compared to expert assessment.

The hypothesis for the first research question stated that there would be fewer discrepancies between the students and experts' evaluation of the designs as the experience level increased. It was believed that having manufacturing expertise would improve the familiarity and therefore improve their self-assessment of their designs [48], thereby aligning with the experts' assessment. It was found that in addition to significant discrepancies in the assessment of the designs, the students significantly reported more DfM axioms compared to the experts.

There are some reasons that explain this phenomenon. One factor could be a lack of intervention to help students in assisting with the self-assessment. As Gordon found in his work comparing the self-assessment of trainees in health professions against the assessment of experts [68], the self-assessment by the trainees was improved when an intervention took place that clarified the criteria for success and compared preliminary assessments by the students to those of the experts. In the context of design, priming students with relevant content before having them begin concept development was shown to have no significant impact on the self-assessment of the designs produced, as was found by the work done from Pearl et al. [50]. Simply presenting axioms to the students at the beginning of the design process is an insufficient method to changing how students perceive DfM axioms in their designs. This finding supports the experimental results obtained from Liao et al. [69], who found that introducing relevant priming content in the middle of the design process changed both the types of designs that were created and the self-assessment of the designs. This signifies that having an intervention in the middle of the design process, can help students improve the self-assessment of the designs.

In the work done by Abadel et al. [70], where they compared the clinical competency of medical graduates' self-assessment against the experts' assessment and obtained similar results, they attributed the discrepancies to the students overestimating their abilities and competency. In aligning with DfM, the work by Sinha et al. [36] confirms the problems of translating what is taught into practice. In their work, they found that students improved the elegance of their designs, but their manufacturability did not change. This emphasizes the importance of needing to identify what is critical to present in an intervention, which will be discussed in the following section.

6.2 Incorporating complex shapes and geometries and considering the minimum feature size can significantly influence the manufacturability of a design.

The hypothesis for the second research question stated that the design axioms that would have significant influence on the manufacturability of a design would be to avoid intricate shapes and to rely on low-labor-cost operations because of their anticipated usage relative to the rest of axioms under observation. The most notable finding from the two generated regression models for predicting the manufacturability of the designs were the two identified axioms that significantly influence manufacturability: incorporating complex shapes and considering the minimum feature size. Regarding the axiom "Incorporate Complex Shapes and Geometries, Tables 6a and 6b this axiom was negatively correlated with TM and positively correlated with AM, respectively. This means that leveraging this axiom will improve the design for AM, while avoiding this axiom will improve the design for TM. This makes sense when considering that DTM favors simple designs, while DfAM favors those that are complex [1]. As for considering the minimum feature size, this axiom was positively correlated for both AM and TM. This significant DfAM axiom makes sense when considering that minimum feature size is frequently associated with AM [71]. As for its significance with TM, this is likely due to the connection between features and the tolerances within these features [72], the latter of which was not explicitly defined as part of the 7 DfTM axioms (tolerances was a subset of the "Ample Spacing Between Holes" design heuristic, where no significant correlations were found from this axiom.

There were also other significant axioms that were present in both manufacturability models. The traditional manufacturability model included avoiding intricate shapes, relying on low-labor-cost operations, and leveraging standard materials, components, and tooling, while the additive manufacturability model added in orienting overhanging surfaces. All these axioms were found to have positive correlations within their respective models. This means that for improving a design's manufacturability, it is important to emphasize these specific axioms based on the selected manufacturing process. For future interventions, the content that should be presented to the students to improve a design's manufacturability for AM is summarized in Table 8.

Table 8. Content Material for DfAM Intervention

DfM Axiom	Intent of Emphasizing Axiom
Incorporate Complex Shapes and Geometries	Encourage in Design
Consider the Minimum Feature Size	Encourage in Design
Orient Overhanging Surfaces	Encourage in Design
Avoid Large, Flat Regions	Encourage in Design
Provide Ample Spacing Between Holes	Encourage in Design
Orient Curved Surfaces	Encourage in Design
Rely on Low-Labor-Cost Operations	Discourage in Design
Avoid Intricate Shapes	Discourage in Design

7. CONCLUSION

The design considerations that accompany AM are critical to implement as it dictates if a design leverages the advantages and opportunities that AM provides. In understanding the purpose of creating suitable designs for AM, it is important to address any natural design tendencies early that may prohibit suitable AM designs from being created. In this work, it was found that incorporating complex shapes and geometries and considering the minimum feature size can significantly influence the manufacturability of a design. These findings provide insight into what needs to be addressed during potential interventions.

Future work will explore the effect of varying the prompt to observe if providing additional criteria leads to improved designs that can be better assessed for their manufacturability. Additional work will further investigate the specific features that students incorporate into their designs (such as rectangular blocks or lattice structures) and the frequency with which they are incorporated. Lastly, interventions will be implemented to observe if they can change the students' perception of axioms in their designs and their potential to successfully have students rethink their designs as they develop them in the concept generation stage.

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