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ANALYZING EXPERT DESIGN COST ESTIMATION FOR ADDITIVE MANUFACTURING

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ABSTRACT

Compared to conventional fabrication, additive manufacturing enables production of far more complex geometries with less tooling and increased automation. However, despite the common perception of AM's "free" geometric complexity, this freedom comes with a literal cost: more complex geometries may be challenging to design, potentially manifesting as increased engineering labor cost. Being able to accurately predict design cost is essential to reliably forecasting large-scale design for additive manufacturing projects, especially for those using expensive processes like laser powder bed fusion of metals. However, no studies have quantitatively explored designers' ability to complete this forecasting. In this study, we address this gap by analyzing the uncertainty of expert design cost estimation. First, we establish a methodology to translate computer-aided design data into descriptive vectors capturing design for additive manufacturing activity parameters. We then present a series of case study designs, with varied functionality and geometric complexity, to experts and measure their estimations of design labor for each case. Summary statistics of the cost estimates and a linear mixed effects model predicting labor responses from participant and design attributes was used to estimate the significance of factors on the responses. A task-based, CAD model complexity calculation is then used to infer an estimate of the magnitude and variability of normalized labor cost to understand more generalizable attributes of the observed labor estimates. These two analyses are discussed in the context of advantages and disadvantages of relying on human cost estimation for additive manufacturing forecasts as well as future work that can prioritize and mitigate such challenges.

1. INTRODUCTION

Compared to conventional processes, such as machining, molding, and forming methods, additive manufacturing (AM) relies less on tooling, provides inherent automation, and can be applied to almost any geometry that fits within the AM machine build volume and resolution limits. In particular, additively manufacturing metal components using laser powder bed fusion (LPBF) presents substantial opportunities for value-driven, industrial applications. Although LPBF components may not always match the mechanical properties [1–3] or baseline fabrication cost [4,5] of machined components, complex LPBF parts do not require additional tooling or time-consuming machine setups compared to simpler parts. Therefore, LPBF does not proportionally increase in manufacturing cost with increased complexity to the same degree as traditional manufacturing processes, especially in builds requiring fewer tooling-driven post-processing operations [6]. This attribute makes LPBF especially promising in sectors with geometric and weight limitations and lower production volumes, such as aerospace [7].

However, despite the complexity achievable by AM machines, LPBF and AM do little to support an important and increasingly challenging portion of the industrial manufacturing process: the design of new components. In fact, the increased freedom to design complex parts can inadvertently become a hindrance to the design process in some cases. When parts become more complex, they deviate from more standardized components. This deviation can demand more analysis, iteration, and one-off design work from engineers, increasing the duration and cost of the design process [8]. Furthermore, design for AM (DfAM) often employs multiple computer-aided design (CAD) activities, such as geometry definition, thermal analysis, slicing, topology optimization, and build preparation, which may not be needed for some conventional processes. Products designed for AM also tend to be most profitably manufactured at low volumes [5,9,10], making the cost of design even more impactful.

Given that LPBF already has potential product performance drawbacks [11,12], stacking demanding and costly design challenges in advance of manufacturing could be particularly detrimental to the overall research and development process. Also, engineering design process quality has been shown to be further decreased when designers lack experience in a new manufacturing process like LPBF [13]. We posit that this combined lack of existing industrial expertise [13] and potential increase in design costs could slow the adoption of LPBF, which has not yet penetrated mainstream industry across all sectors.

One way to address this gap is to provide designers with a means to reliably estimate required design labor for an LPBF-focused project prior to actually completing design activities. Ideally, this design estimation technique would be repeatable, quick, and automatic. Creating such a tool to estimate complicated human factors like detailed CAD labor is not trivial. In this study we seek an important first step in realizing such a tool: characterizing human estimates of design labor cost for LPBF designs.

Specifically, this work addresses the following research questions:

1. *To what degree do LPBF experts vary on estimates of engineering labor required to complete typical DfAM activities for individual components of varying geometric complexity?*

2. *Given attributes of a design concept to be forecast and the individual expert conducting the forecasting, how consistent and predictable is an expert's forecast and what are the most significant attributes?*

3. *What is the range and variability of estimated time per human design action, both within and between subjects?*

The remainder of the paper is organized as follows: First, we discuss prior literature regarding manufactured product cost modeling and DfAM/LPBF-specific design process challenges. Next, we document our methodology to analyze design geometry in context of DfAM labor activities, measure expert cost prediction values, and analyze significant factors of expert cost analysis. Finally, we discuss our results and their implications on potential limits of human design labor cost estimation in the context of other challenges in the growing adoption of LPBF in industrial applications.

2. BACKGROUND

In this section we synthesize prior literature regarding manufactured product cost modeling approaches (see section 2.1) and specific challenges of design for laser powder bed fusion additive manufacturing of metals (see section 2.2).

2.1 Manufactured Product Cost Modeling

The vast majority of products are still manufactured using conventional techniques [14], meaning that AM does and will continue to coexist with conventional processes when used by industrial organizations. Thus, understanding the context of literature related to modeling costs from manufacturing and design at large is essential to researching similar issues for AM.

The second half of the twentieth century marked a gradual development in design strategies that are specifically oriented toward maximizing the practicability and efficiency of the manufacturing process for an engineered system [15–17]. As Kuo et al. point out [15], the focus began with "producibility" of components before evolving toward a consideration of a design's consequences on the entire manufacturing process [15]. Dewhurst and Boothroyd, early pioneers of the Design for Assembly (DFA) subset of DFM, asserted that DFM is completed in two steps: a) identifying suitable materials and manufacturing processes, and b) designing individual components within the limits of the available resources [18]. This mentality leads to a commonly accepted strategy in which DFM is not one single technique, but rather a broad range of methodologies with which engineers design with particular manufacturing processes in mind, commonly called "Design for X" (DFX) [19–21]. In addition to manufacturing-related DFX concepts discussed here, DFX has also been expanded to cover many other industrial and societal concerns, such as design for sustainability [22], design for maintainability [23], and design for accessibility [24]. Under the Design for X mentality, the focus for cost estimation predominantly lies in a) the cost of the individual components, b) the cost of assembling components, and c) the end-to-end efficiency of the overall manufacturing process. Individual studies often focus on either a single process, such as machining [25], injecting molding [26], or casting [27], or a single type of material such as steel [28] or carbon fiber [29].

Although there exists substantial breadth of research in process and material-specific cost concerns, most works tend to focus on the upfront and ongoing costs of the actual manufacturing only, and not the cost of engineering design labor that precedes those operational manufacturing activities. Unlike most modern manufacturing techniques, which are tightly integrated with relatively predicable machines, the engineering design process is a largely human-driven activity, relying heavily on individuals and teams. To estimate costs related to these complex human factors, project management costing techniques may be used. One useful approach is activity-based costing (ABC) [30–34]. ABC involves the breakdown of work into a collection of activities called a work breakdown structure (WBS) [33], the assignment of costs to each activity, and the forecasting or monitoring of the resources spent on each activity [33,34]. Although ABC is certainly useful for cost-minimizing strategies employed after the design stage [32,35], it is also particularly well-suited for cost analysis of human design labor because it can be used in situations that are not directly tied to production volume [33], such as the upfront design process [34]. Ben-Arieh et al. presented a framework to use ABC when designing machined products, breaking down the design activity into specification development, conceptual design, and detail design stages [34,36]. They also further break down the design stages into the tools, resources, and personnel needed during those stages. Providing increasingly detailed breakdowns of cost could enhance the resolution of ABC for human-driven design. However, doing so may not be straightforward and may substantially depend on the nature of the particular manufacturing processes used, individual human participants, and organization management structures. As Armstrong points out ABC can hinder competitive practices that deviate from the standard activity types, hide useful information about indirect costs, and may be perilous if combined with management practices, such as tying labor activity data to performance evaluation [37].

2.2 Specific Challenges in Design for Laser Power Bed Fusion Additive Manufacturing of Metals

Although costing and project management are both relevant to all manufacturing processes, LPBF AM has specific attributes that motivate its study in the current work. First, engineers who seek to use LPBF often aim to take advantage of one or several opportunistic attributes of AM [14]. For instance, mesostructural features like cellular cutouts [38] and lattices [39] can provide lightweight and strong features and are most easily added through layer-by-layer manufacturing like LPBF. Additionally, the high strength and excellent thermal resilience of metal components allows them to excel in demanding environments, such as aircraft [7]. The beneficial properties of metals also make them good candidates to conduct redesign efforts that incorporate part consolidation, in which multiple components in an assembly are redesigned into a single, connected component that performs the same function [40].

Although these opportunities are promising, they come with several downsides related to increased design challenges. First, parts that are produced through LPBF tend to be more expensive to manufacture than those made by traditional processes [5]. This limitation places greater importance on the activities of the designer, who may have to reduce resources in other components of the design to make up for increased cost of manufacture. Additionally, LPBF AM metal components can be susceptible to mechanical failures due to manufacturing defects, such as voids and cracks [41], that are very challenging to identify with non-destructive evaluation [42]. These issues could increase the risk of using LPBF AM metal components in performance-critical applications, potentially driving up the amount of labor required to analyze the components. Such analysis must be done both for the performance of the LPBF machine, process settings, and selected material to produce the design and for its final performance in the chosen application. Ultimately, this drives up the total design costs associated with the component.

Costing engineering projects on an activity and component-based level of granularity is essential to ensuring an efficient and effective research and development process. Being able to preemptively estimate how much human design labor will be required when both the design tasks and final manufacturing process are demanding, as is the case in computer-aided design for LPBF AM, is especially important.

In this study, we take the first steps in understanding how well experts in the field of LPBF AM of metals can currently estimate the required engineering design labor for individual components. Although seeking causal understanding is unrealistic for a preliminary study, we instead seek a breadth of knowledge by establishing a methodology to objectively quantify the complexity of components and the background experiences of participants and then measure design labor predictions across these factors. Through investigating the general human variability in this task, the resulting trends may be used to identify significant factors and plan larger or more targeted studies in the future that seek causal understanding that is sufficient to help build the next generation of assistive design tools, such as those based on artificial intelligence constructs.

3. METHODOLOGY

We characterized the performance of experts when estimating design labor for LPBF components and statistically analyzed the significance of design attribute and participant background factors. This section describes the details of the expert design cost estimation measurement process (see section 3.1); design attribute description methodology (see section 3.2); and the analytical approach (see section 3.3).

3.1. Expert Design Labor Estimate Measurement Process

Data to investigate expert design cost prediction capabilities was obtained using a survey of LPBF experts who were tasked with making predictions about LPBF design case studies. The survey consisted of two primary sections. In the first section, participants were asked nine demographic questions. The first three of these questions polled participant years of experience in industry, gender, and ethnicity, while the other questions queried aspects of the respondent's experience and self-assessed expertise.

In the second section, participants were shown a series of nine LPBF design case studies. Each successive case study was shown in a random order to each participant, but the questions within each case study block were shown in a consistent order.

Each case study question block contained a pencil sketch-style image of the design concept from isometric and orthographic viewpoints (see Figure 1). This pencil sketch was presented to the participants as the starting point of the engineering design process, intended to mimic the result of a conceptual design brainstorming process. The concept sketch image was followed by isometric and orthographic CAD render views with some dimensions (see Figure 2). The dimensions on these views were not presented to provide detailed documentation, but rather as references to give participants a general sense of the designs' scale. These CAD render views were presented to the participants as the ending point of the engineering design process, with the intent of conveying the result of a detailed design process.

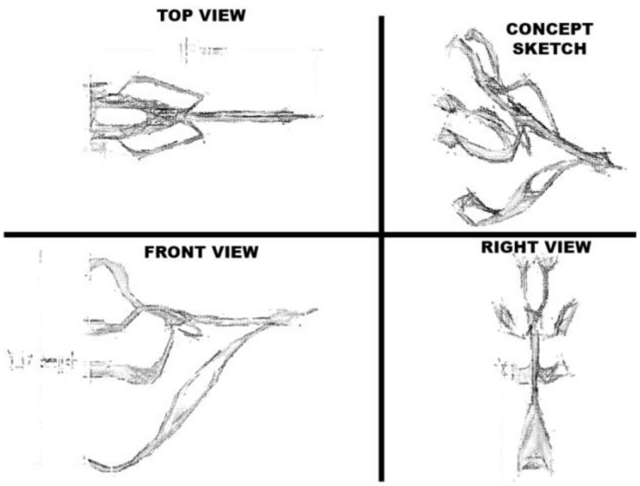

FIGURE 1. EXAMPLE CONCEPT SKETCH IMAGE OF ONE OF THE CASE STUDY DESIGNS, THE GENERATIVE BRACKET, THAT WAS SHOWN TO SURVEY PARTICIPANTS AS THE STARTING POINT OF THE DESIGN PROCESS.

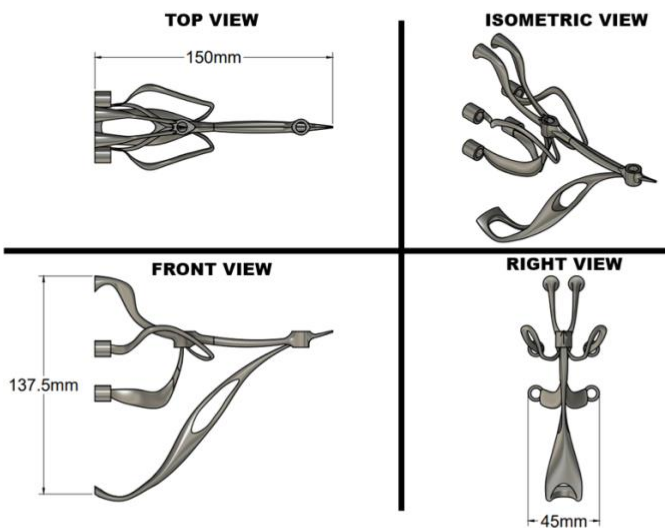

FIGURE 2. EXAMPLE IMAGE OF FOUR ORTHOGRAPHIC VIEWS OF ONE OF THE CASE STUDY DESIGNS, THE GENERATIVE BRACKET, THAT WAS SHOWN TO SURVEY PARTICIPANTS AS THE ENDING POINT OF THE DESIGN PROCESS.

After being shown each design, participants were asked to estimate how long in hours it would take an average engineer to design the pictured component. For this question, they were also asked to assume that the engineer begins the design process with the concept sketch of the design and ends with the CAD model shown below it. Next, the participant was asked to divide their total estimate into the following five categories by percent of design labor time: a) 3D solid modeling and computer-aided design (CAD), b) engineering analysis and simulation, c) manufacturability analysis and cost estimation, d) build orientation and support structure generation, and e) slicing and toolpath generation. These design activities were chosen because they represent a common workflow for LPBF [43].

Next, participants were asked the extent to which they were confident in their design time prediction, whether the design was well-suited for metal AM LPBF, and whether the design was well-suited for manufacturing with conventional processes. Each of these three questions were presented as a 5-level Likert scale, where a 1 represented the participant strongly disagrees that the design was well-suited for the process and a 5 represented that the participant strongly agrees that the design was well-suited for the process. Finally, participants were asked to rate the geometric complexity of the design on a 5-level Likert scale, where a 1 represented that the participant thought the design was very simple and a 5 represented that the participant thought the design was very complex. The survey was distributed to industry experts in LPBF.

3.2. Case Study Design Attribute Description Methodology

Although many products rely on assemblies, composites, or nonsolid entities, designing such products adds substantial diversity, complexity, and case-by-case specificity to the nature of the design process. Because of this, we limited the focus of case study designs to products which consist of a single, solid component that is made from a single material. This decision means that certain opportunistic attributes of AM are not as relevant to this study, such as multi-material complexity or part consolidation. Instead, we focus on DfAM opportunities related to hierarchical complexity and shape complexity. These opportunities are often achieved through the use of mesostructures [44] and topology optimization [45], which we incorporate in our case studies.

In addition to categorically defining the scope of the current work, we also sought to study a varied range of different case study designs. Furthermore, we sought to understand if there were concise, quantifiable attributes related to design complexity that might be found to correlate with participant cost estimate results. To achieve this goal, we used three different quantitative complexity metrics: C_{PR}, the volume ratio complexity factor; C_{AR}, the area ratio complexity factor; and C_{DOF}, the CAD degrees of freedom complexity factor.

Since selecting a single complexity factor could itself introduce bias, multiple types of complexity factors are considered and combined into a *design attribute description vector* which offers a holistic representation of a design's complexity. Specifically, the design attribute description vector uses two geometric complexity factors and one design process activity-based factor. The geometric complexity factors of part volume ratio and part area ratio are defined as

$$C_{PR} = 1 - \frac{V_p}{V_b} \tag{1}$$

and

$$C_{AR} = 1 - \frac{A_s}{A_p} \tag{2}$$

where V_p is the part volume, V_b is the part bounding box volume, A_s is the volume of a sphere of equal surface area to the part, and A_p is the part surface area. These geometric complexity factors were chosen because they are related to surface area and volume, both of which are aspects that affect the visual appearance of a design. Including factors with this attribute is important because the current work uses visualizations of designs to communicate them to participants. Attributes related to surface area and volume are also known to relate to AM costs from other work [46]. C_{PR} and C_{AR} are related to the implementation of the design surfaces used to model the part. The current work used parametric, mathematically defined surfaces modeled in Autodesk Fusion 360 [47] for these calculations.

The CAD degrees of freedom complexity factor, C_{DOF}, is a design-activity-based factor because it directly relates to the user interface activities required to model the design concept. In summary, C_{DOF} estimates the number of steps a human must take to model the part. This measurement is specific to both the CAD modeling paradigm chosen and the specific combination of features chosen to achieve the desired model. In this study, Autodesk Fusion 360 [47] was used with a parametric, feature-based modeling paradigm. A "degree of freedom" in this context refers to a numeric parameter that the designer must set to define a particular feature used to model the part with the user interface of a CAD application. Compared to the geometric complexity factors, C_{DOF} is not as visually recognizable from an image of a model, but does relate more closely to the actual required duration to design a component using CAD. This assertion is based on the assumption that setting each parameter in a design requires some duration of human-attentive effort. Specifically, C_{DOF} is computed by counting the number of CAD modeling features of various types in a model, then multiplying the counts by the assumed degrees of freedom required to define each feature type. This procedure is summarized by the equation

$$C_{DOF} = \sum_{i=1}^{n} v_i m_i \quad (3)$$

where n is the number of allowable CAD feature types, v_i is the number of degrees of freedom assumed to be required for the feature ith type, and m_i is the number of instances of the ith feature type. Different features require different numbers of numeric parameters to define. For instance, a point on a 2D plane, called a "Sketch Point" in many CAD applications, requires two numeric dimensions, x and y distances relative to an origin, be defined. Other features, such as a simple extrusion or revolve of a profile may require only one dimension, while others, such as a 2D linear pattern, may require more. Again, the specific types of features used, numbers of degrees of freedom that are included and important to those features, and combinations and sequences of those features used in an actual design is not unique for a particular geometry. These factors depend on the particular CAD application used and choices made by the designer. In this study, we used a sketch-based, parametric modeling approach.

In this approach, 2D reference planes are first defined within a 3D build space. Next, sketch points representing the vertices of profile curves are located and drawn on the reference planes. Mathematically-defined curves are then drawn connecting these points into either closed profiles or non-closed paths for construction. The profiles and paths are then extruded, swept, revolved, or lofted to define 3D volumes. These 3D volumes are then combined to form a macrostructure volume. The macrostructure is either accepted as the final design, or is modified by patterning lattice cutouts to form a mesostructure or selectively trimmed based on a finite element analysis simulation of stress under loading. This process is a common approach to parametric CAD DfAM. Different CAD modeling paradigms, such as constructive solid geometry (CSG) of primitives, surface modeling, implicit modeling, or approaches which allow for combinations of paradigms may require different assumptions surrounding degrees of freedom per allowable feature if using a similar approach.

The case studies were single-component products. Participants were prompted to estimate the design labor in hours required to create the part. To avoid possible bias in participants having seen certain designs before, we did not use existing commercially manufactured products nor previous designs from prior literature.

To provide both consistency and replication in the design complexity, we used a three-level design complexity progression that was replicated for three different design functional types. This progression of design complexity included (a) macrostructure CAD only, (b) mesostructure CAD, and (c) generative CAD. The macrostructure-only CAD designs were created using parametric CAD features only, lacking mesostructural complexity achieved through patterned features and generative features. The macrostructure designs were the least complex in their functional categories, as measured by the three quantitative complexity factors.

The mesostructure CAD designs included a patterned, subtractive lattice feature, incrementally increasing the complexity due to increased surface area. The generative CAD used a hybrid design approach that incorporated a combination of simulations, functional constraints, subtractive features, and additive features to guide and form the final shape. These included a stress-based topology optimization to lightweight the part given an assumed loading scenario to inspire broad lightweighting strategies followed by subsequent stress simulations to include additive support features. These designs were the most geometrically complex, largely due to their high-dimensional splines and curved surfaces. The design intent of these forms for the study were that they efficiently withstood a load case and appeared "organic" to the participants. These complexity levels were replicated three times for the artifact types of "bracket", "bottle opener", and "hatchet". The artifact types were selected because they could plausibly be single component products suitable for the scope of the study, were of reasonable scale for a contemporary LPBF machine's build volume, and would have mechanical user requirements derived from the resistance of external forces (see Figure 3).

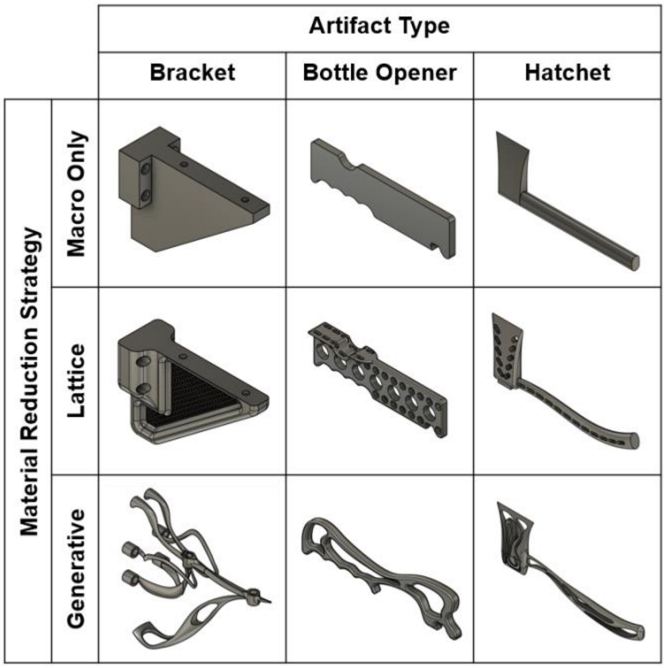

FIGURE 3. ISOMETRIC IMAGES OF THE CASE STUDY DESIGNS PRESENTED TO SURVEY PARTICIPANTS FOR DESIGN LABOR ESTIMATION.

3.3. Data Analysis

The survey data were analyzed for four primary considerations: a) the attributes of the participants, b) the consistency and predictability of the labor estimates, c) the significance of design and participant factors on labor estimates, and d) the comparative time per CAD degree of freedom for each participant. Understanding the participant sample attributes is important to contextualizing the results. Although the scope of the current work does not intend to assign causal relationships for the effects of all demographics measured, we anticipated that participant focus industry attributes, such as the degree to which an industry is regulated, might positively correlate with design labor estimates. However, we also anticipated that the resource limitations of the current work would likely render correlations not statistically significant at this time.

Additionally, we investigated the significance of factors related to a) the design for which the labor was estimated and b) the individual conducting the estimation. To determine significance, we analyzed the data using a linear mixed effects model (LMEM). The response variable for the LMEM was the number of design labor hours estimated by a participant. The fixed effects were the artifact type (bracket, bottle opener, or hatchet), design material reduction strategy type (macrostructure only, lattice, generative), volume ratio complexity, area ratio complexity, degrees of freedom complexity, participant years of experience, participant design for AM self-assessed expertise, participant design for conventional processes self-assessed expertise, participant CAD self-assessed expertise, and participant cost estimation self-assessed expertise. The per-subject random effects were participant-assessed design complexity, participant-assessed AM manufacturability, participant-assessed conventional manufacturability, and participant labor estimate confidence. The variables that were included as random effects were all participant reported for each design, and not intrinsic to the designs.

The LMEM was conducted using R version 4.0.5 and the lmerTest version 3.1-3 library. Significance of the coefficients of each fixed effect were determined using Satterthwaite's method t-tests and an alpha value of 0.05. Significance in this test suggests that the fixed effect contributes to the participant's labor estimate. Analysis of variance (ANOVA) was used to determine if the random effects influenced labor estimates differently for each participant.

Next, we explored the relationship between quantitative complexity and design effort by comparing each participant's predictions to the number of degrees of freedom calculated for the design. This calculation is called t_N, the normalized degrees of freedom complexity factor, calculated as

$$t_N = \frac{t_{est}}{C_{DOF}} \tag{6}$$

where C_{DOF} is the degrees of freedom complexity factor for the design model and t_{est} is this participant estimated labor required to design the part in hours. C_{DOF} was chosen for this calculation because it is the closest to a common denominator which can compare all parts. The units of t_N are hours per degree of freedom, and allow us to compare both within group and between group central tendency and spread of participant responses similar to a labor rate. Although C_{DOF} is only an approximate estimate of the number of degrees of freedom required to produce the CAD model in question, it provides a useful benchmark for the purposes of interpreting these data and comparing across subjects. We hypothesize that high variability of t_N would be less desirable in industry when actually using human labor estimates for forecasting, as it would suggest high individual-to-individual bias and could erode trust in the estimates.

4. RESULTS AND DISCUSSION

In this section we detail the results participant demographic breakdown (see section 4.1), the labor estimation results (see section 4.2), the linear mixed effects model results (see section 4.3), and the estimated cost per design task results (see section 4.4).

4.1. Participant Sample Background Results

In total, 25 participants fully completed the survey (partially complete responses were omitted). This sample included 19 participants self-identifying as men, 3 participants self-identifying as women, 0 participants identifying as another, and 3 participants selecting to prefer not to say. 19 of the participants self-identified as white, 1 self-identified as Hispanic, Latino, or Spanish origin, 1 self-identified as Middle Eastern or North African, 1 self-identified as some other race, ethnicity, or origin, and 2 selected to prefer not to say. For industry affiliation, 10 participants self-identified as Aerospace, 6 self-identified as Defense, 2 self-identified as Education, 2 self-identified as Consumer Goods, 1 self-identified as Energy, 2 self-identified as Transportation, and 1 self-identified as "software and DfAM agnostic of industry". The mean number of years of experience in industry was 11.4 years, ranging from a minimum of 0 years to a maximum of 33 years. The mean participant age was 35.1 years. For the participant background five-level Likert scale questions, the responses were converted to a normalized value ranging from 0 to 1. Frequencies for these responses are shown in Figure 4.

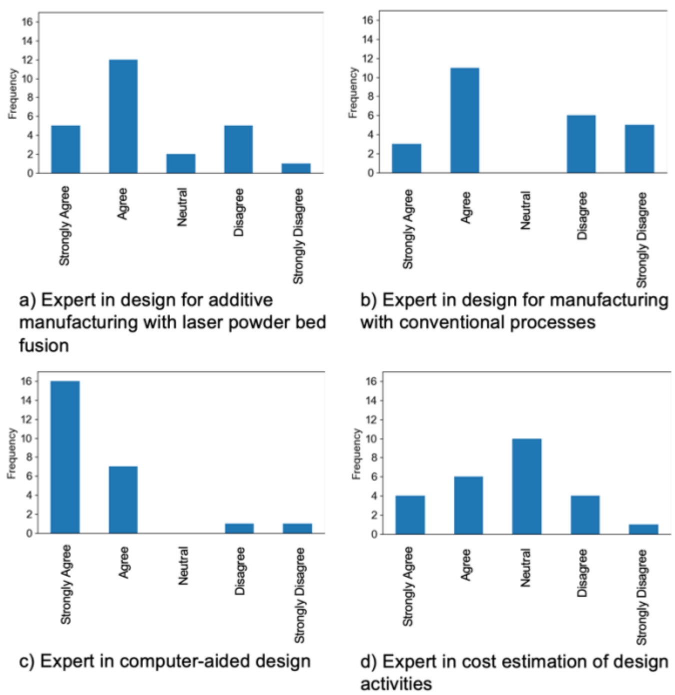

FIGURE 4. PLOTS OF PARTICIPANT SELF-REPORTED RESULTS TO WHETHER THEY AGREED THAT THEY ARE AN EXPERT IN A) DESIGN FOR ADDITIVE MANUFACTURING OF METALS WITH LASER POWDER BED FUSION, B) DESIGN FOR MANUFACTURING WITH CONVENTIONAL PROCESSES, C) COMPUTER-AIDED DESIGN, AND D) COST ESTIMATION OF DESIGN ACTIVITIES.

4.2. Participant Sample Cost Estimation Results

The participants' estimates of required engineering design labor varied substantially both across artifact types and within design concepts (see Figure 5). Overall, the mean estimate for design labor of all concepts across all participants was 19.6 hours and the standard deviation was 21.2 hours. The generative bracket design concept had the longest estimated duration, with a mean estimate of 48.16 hours. Conversely, the macrostructure-only bottle opener design concept was the shortest estimated duration, with a mean estimate of 7.8 hours recorded. The most variable design was the generative bracket, for which a standard deviation of 35.83 hours was observed. The design groups of bracket, bottle opener, and hatchet exhibited means of 27.72 hours, 12.63 hours, and 18.49 hours respectively. When grouped by design-intent complexity, the estimated labor followed the central tendency trend of generative designs (30.87 hours), followed by lattice designs (19.09 hours), followed by macrostructure-only designs (8.88 hours). This trend was observed both overall and within all design groups except for the bottle opener, in which the generative and lattice designs were relatively closer on average.

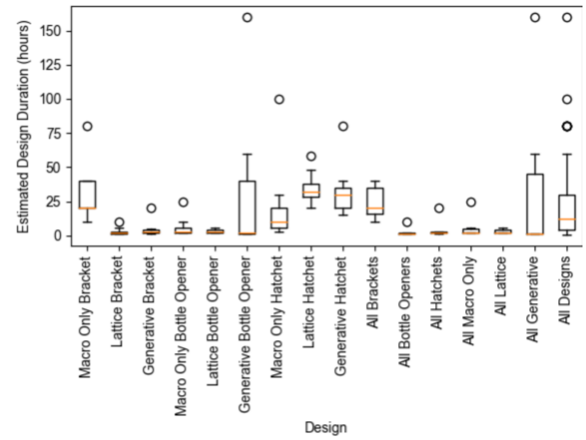

FIGURE 5. BOX PLOTS OF DESIGN LABOR ESTIMATION SURVEY RESULTS FOR EACH CASE STUDY DESIGN AND SELECT AGGREGATES OF MULTIPLE DESIGNS.

In terms of design labor breakdown, participants indicated that engineering analysis and simulation was estimated to be the most time-consuming portion of the DfAM process, consuming 34% of the design labor, on average (see Figure 6). Slicing and toolpath generation was the least time-consuming portion, with a mean of 9%. The magnitude of variability for design breakdown allocations was less than the variability observed for overall labor hours estimates. For instance, the mean standard deviation of design hours required for a single design concept was 108% of its mean, whereas the mean standard deviation for a single design labor activity was 62% of the respective mean.

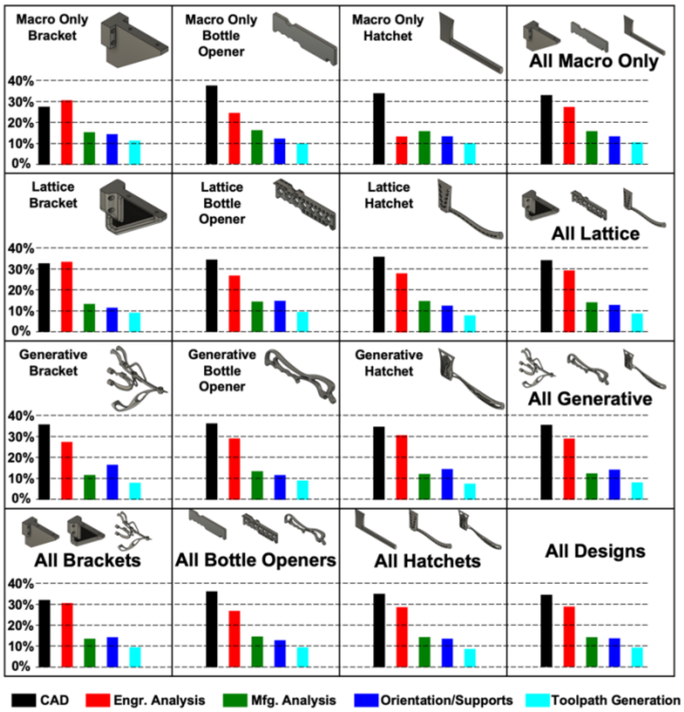

FIGURE 6. PLOTS OF MEAN DESIGN LABOR BREAKDOWN ESTIMATION RESULTS FOR EACH CASE STUDY DESIGN AND SELECTED AGGREGATES OF MULTIPLE CASE STUDY DESIGNS.

Participants were above neutral in the self-assessed confidence of their predictions. When converted from a five-point Likert scale to a normalized value, the mean confidence was 0.67 and the standard deviation was 0.21. A spread of perceived complexity, suitability for AM, and suitability for conventional manufacturing values were observed, covering the entire range of available responses.

4.3. Labor Response Predictability Analysis

The linear mixed effects model (LMEM), which was used to model whether participant and design attributes significantly affected participant estimated design cost, indicated a mix of both significant and insignificant factors were observed. Six of the fourteen of the factors investigated in the LMEM were significant to an alpha value of 0.05 (see Table 1). These significant factors included artifact type, hierarchical complexity, degrees of freedom complexity factor, participant perceived complexity, participant years of expertise, and participant degree of AM expertise. Many of these significant factors were data that were either provided by the participant directly, such as their levels of expertise, or directly evident to the participant, such as artifact type. Other attributes of the designs that were not directly communicated to the participants, such as area and surface volume ratio complexity, were not significant. These results suggest that the combination of a participant's background and their own mental model of a design's complexity were more impactful on their design labor duration estimate than general quantitative complexity values. One significant attribute that differs from this trend is degrees of freedom complexity factor. This factor's significance suggests that unlike part and volume ratio complexity, the complexity factor based off the CAD modeling paradigm was correlative to this participant pool's predictions even though it was not explicitly revealed to them. Although more detailed studies would be required to definitively assign causality, this difference could mean that the degrees of freedom complexity metric is more likely to be intuitive to experienced designers when assessing design complexity and required design duration based on their visual appearance.

TABLE 1. LINEAR MIXED EFFECTS MODEL COEFFICIENTS AND T-STATISTIC RESULTS FOR THE LINEAR MODEL PREDICTING PARTICIPANT LABOR ESTIMATE GIVEN DESIGN CONCEPT AND PARTICIPANT BACKGROUND DATA. BOLDED P-VALUES WERE SIGNIFICANT TO α = 0.05.

Independent Variable	Model Coefficient	t-statistic	p-value
Artifact Type	-0.018	-2.010	**0.046**
Hierarchical Complexity	-0.072	-2.710	**0.007**
Part Volume Ratio Complexity Factor	0.021	0.657	0.512
Part Area Ratio Complexity Factor	0.126	0.949	0.344
Degrees of Freedom Complexity Factor	0.224	3.118	**0.002**
Participant Perceived Complexity	0.117	2.488	**0.016**
Participant Estimated AM Manufacturability	0.033	1.147	0.270
Participant Estimated Conventional Manufacturability	-0.016	-0.576	0.566
Participant Confidence	-0.046	-1.004	0.334
Participant Years of Experience	0.110	3.530	**0.002**
Participant Degree of AM Expertise	0.172	5.472	**3.000e-5**
Participant Degree of Conventional Manufacturing Expertise	0.039	-1.573	0.132
Participant Degree of CAD Expertise	-0.035	-1.008	0.329
Participant Degree of Cost Estimation Expertise	-0.032	-0.878	0.393

In addition to whether factors were significant or insignificant, the LMEM also provides estimates as to the magnitude and directionality of each factors' effect. Positive and relatively large coefficients were observed with the degrees of freedom complexity factor, participant perceived complexity, participant years of experience, and the participant degree of AM expertise. Although the degrees of freedom metric used in this study has not been validated experimentally, that the measure consistently and strongly correlates with participant estimated design labor costs is promising for its effectiveness as a concise and reliable design attribute for future work. The positive correlation matches our intuitive hypothesis that the perception or suggestion of more CAD tasks would lead a design forecaster to a higher design cost estimate. Participant perceived complexity sharing a similar directional trend also supports this hypothesis. Participant years of experience and degrees of AM expertise having a positive effect on estimated design cost also supported our intuition. Professionals that have fewer years of experience have been observed to exhibit overconfidence in their field [48]. Conversely, in this case those engineers with more experience might become more risk averse over time, and therefore provide more conservative and costly estimates for labor.

4.4. Estimated Cost Per Design Task

In addition to investigating which design and participant attributes best predicted estimated cost, we also calculated and characterized an estimate of the time allotted for finer detailed CAD operations as based on the participant labor estimates and an estimate of the degrees of freedom of the CAD models. The CAD models for the design case studies used in the current work exhibited a range of C_{DOF} and t_N values (see Table 2). The macro-only hatchet was the lowest number of degrees of freedom, 96, while the generative hatchet was the highest, 1,073. The time per degree of freedom for all participants across all designs was 3.24 minutes per degree of freedom. In terms of individual designs, the greatest value was for the macro only hatchet, at 5.75 minutes per degree of freedom and the lowest value was for the generative bottle opener at 1.42 minutes per degree of freedom.

TABLE 2. CALCULATED RESULTS FOR VOLUME RATIO COMPLEXITY (C_{PR}), AREA RATIO COMPLEXITY (C_{AR}) AND MEASURED PARTICIPANT ESTIMATED RESULTS FOR MEAN NORMALIZED PARTICIPANT RATED COMPLEXITY AND MEAN TIME PER DEGREE OF FREEDOM.

Design	Volume Ratio Complexity (C_{PR})	Area Ratio Complexity (C_{AR})	Mean Normalized Participant Rated Complexity	Mean Time per Degree of Freedom (t_N, minutes)
Macro-only bracket	0.703	0.499	0.08	5.16
Lattice bracket	0.805	0.692	0.65	4.11
Generative bracket	0.986	0.795	0.93	3.54
Macro-only bottle opener	0.0958	0.616	0.08	4.72
Lattice bottle opener	0.804	0.748	0.45	2.26
Generative bottle opener	0.721	0.690	0.47	1.42
Macro-only hatchet	0.722	0.573	0.18	5.75
Lattice hatchet	0.854	0.713	0.54	4.28
Generative hatchet	0.913	0.793	0.76	1.62

The distribution of the estimated time per degrees of freedom for all designs aggregated together most resembled an exponential distribution (see Figure 7). Most values fell between zero and five minutes per action, with nearly 30% of the data falling under one minute per task. Since all of the computer-aided design degrees of freedom could likely be physically completed in seconds by an experienced user who had already planned their actions in advance, these results strongly suggest that time estimated to complete the design by the participants would entail critical thinking or other non-CAD activities, as has been observed in experimental studies of CAD for AM activities [49]. Since outliers do exist in the overall data, and the distribution could be modeled as an exponential, we hypothesize that detecting outliers or deviations from a curve could be useful to screen potentially erroneous design cost estimates. Additional studies would be needed to guide the efficacy of such an approach.

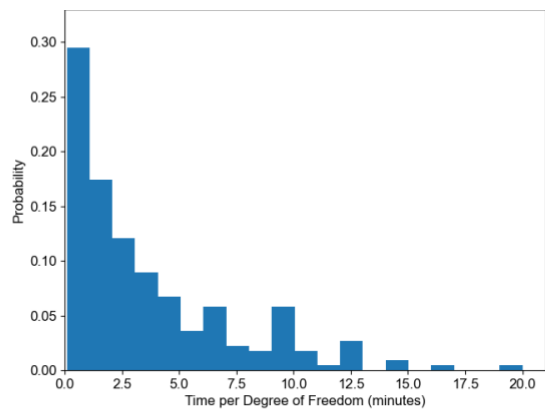

FIGURE 7. PROBABILITY HISTOGRAM OF THE AVERAGE ESTIMATED MINUTES PER DEGREE OF FREEDOM (t_N) FOR EACH PARTICIPANT LABOR ESTIMATION OF A DESIGN, WITH ALL DESIGNS GROUPED TOGETHER.

In addition to examining the distribution of the overall time per degree of freedom results, we also broke down the data into aggregates by design type and design complexity level (see Figure 8). Upon visual inspection, not all aggregates matched the characteristic exponential distribution shape as closely as the overall aggregate. Bottle opener, hatchet, generative, and macro only designs most closely matched the exponential shape, and the others did not appear to match a canonical distribution as closely. Generally, the bracket and hatchet designs exhibited similar distributions to each other when compared with the bottle opener aggregate distribution. The bottle opener aggregate had the highest probability of a degree of freedom taking less than one minute on average, further reinforcing the conclusion that the participants especially thought the bottle openers could be designed quickly. The likelihood of fast average degree of freedom times increased from macro-only, to lattice, to generative. This trend, when combined with the aforementioned result of overall mean estimated times increasing in the same order, suggests an inconsistency and possible shortcoming in the participants. Although the participants were unaware of the degrees of freedom calculation, if it is assumed to be a sufficient proxy of the number of activities required to complete the design work, a consistent estimator should theoretically exhibit a roughly constant average time per degree of freedom. Instead, the participants do not appear to be increasing their estimates on average enough. However, the opposite could also be the case: that participants were overestimating the time for the lower degree of freedom designs. An additional study that experimentally verifies these phenomena in real-world design activities would be required to answer this new question.

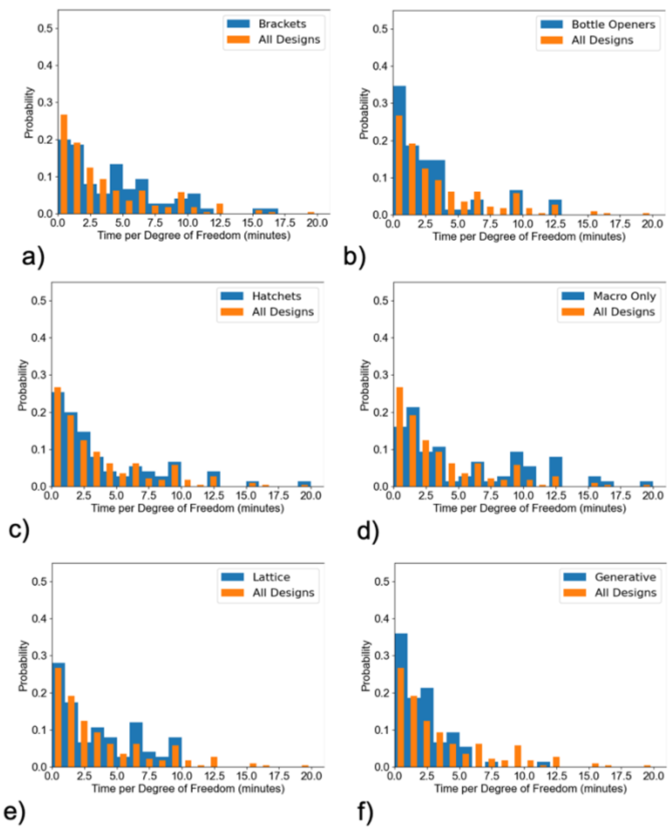

FIGURE 8. PROBABILITY HISTOGRAMS OF THE AVERAGE ESTIMATED MINUTES PER DEGREE OF FREEDOM (t_N) FOR EACH PARTICIPANT LABOR ESTIMATION OF A DESIGN IN THE AGGREGATES OF A) ALL BRACKET DESIGNS, B) ALL BOTTLE OPENER DESIGNS, C) ALL HATCHET DESIGNS, D) ALL MACRO-ONLY DESIGNS, E) ALL LATTICE DESIGNS, AND F) ALL GENERATIVE DESIGNS

5. CONCLUSION

Estimating the cost of designing manufactured components is important to profitable research and development, especially when those design costs may require the up-front scoping of demanding engineering activities like laser powder bed fusion. In this study we investigated the ability of people to preemptively estimate the design cost of metal LPBF AM components and what factors of people and components may influence those estimates. First, we created nine LPBF case study design concept components and CAD models of those designs. Next, we characterized the complexity of the CAD model geometries and topologies. We then distributed a survey to designers in industry who were experienced with the LPBF design process and measured their estimates for design labor and labor breakdown for each of the case studies. Finally, we analyzed the results of the design labor survey to understand the attributes of our sample, the distribution of the labor estimates in the sample, and estimate which factors related to the participants and the case studies were significant to their estimates.

In terms of our first research question, related to how much experts vary in their estimates of labor, we found that the estimates varied substantially and inconsistently. For some case studies, experts differed in their labor estimate by two orders of magnitude, while others were less widely spread. This finding suggested that who was performing the estimate could greatly impact the magnitude of a research and development forecast even for relatively small-scale designs like those studied, differing by multiple weeks of engineering labor. Regarding our second research question, we found that if given summary attributes of a designer and a design problem we could predict their estimate. This result suggests that designers' estimates are not varying due to random chance alone, but rather their experience, background, industry, or bias are likely major factors in their preconceived notion of design cost. Finally, for our third research question we found that there was substantial variability both within and between subjects for the normalized time per CAD action. This observation indicates that human subjects would, overall, not yield consistently accurate design cost estimations in an experimental environment.

Overall, our results suggest that design labor cost estimation is a challenging task, with a potential for inconsistency due to personal bias and multiple factors. Given the importance of forecasting for allocation of research and development resources, further work is needed to both understand the nature of this challenge more precisely and investigate techniques to assist designers in this task. Future studies could directly expand on our findings by testing whether the factors we determined to be significant predictors of preemptively estimated cost are also significant predictors of measured, post-design labor cost. Our methodology could also be enhanced by identifying ways to maximize the overlap of relevant case studies with actual projects in industry so as to reduce the cost burden of conducting such time-consuming studies within the context of busy industrial or academic settings. Furthermore, future work could investigate if our survey results are replicated when posing the case studies and questions in the context of other subfields of AM, non-additive manufacturing environments, or environments not related to physical manufacturing but with a design component, such as software design. Lastly, interventional tools such as data-driven regression analyses could be developed and tested to enhance the consistency and accuracy of preemptive LPBF design labor cost estimation.

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