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Research paper

An auto hierarchical clustering algorithm to distinguish geometries suitable for additive and traditional manufacturing technologies: Comparing humans and unsupervised learning

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ABSTRACT

The development of additive manufacturing has made these technologies suitable for fabricating end products. This encourages companies to identify quickly parts in large databases for which switching from traditional manufacturing technologies to additive manufacturing is convenient. Typically, the manufacturing process selection is made by experts who weigh various parameters, but evidence suggests that intelligent systems could beneficially replace or aid this manual selection. One challenge in using manufacturing data for advanced analysis and machine learning is that it is usually unlabeled, and manual data labelling is expensive and time-consuming. This paper deals with the application of an enhanced unsupervised learning algorithm that automatically identifies parts suitable for additive manufacturing based on parts geometry as a preliminary step of process selection. One hundred randomly selected parts were evaluated by manufacturing experts through a survey and then clustered by the proposed algorithm. The comparison of the manual and algorithmic classifications, using unsupervised learning, regarding suitability for additive or traditional manufacturing is the main original contribution of this study. Overall, 78% convergence between most experts' designations and the unsupervised learning algorithm is achieved. For those parts where expert opinions are substantially aligned, the algorithm showed a 90% convergence rate with human choices. These outcomes support the introduction of an intelligent system to perform a preliminary identification of suitable manufacturing processes based on part geometry, as it can be seen beneficial if compared with the time and cost spent when involving a pool of experts.

1. Introduction

1.1. Machine learning to support manufacturing process selection

The selection of a manufacturing process is one of the critical decisions made during product development [1]. It requires the investigation of both technical and economic constraints [2]. Human experts typically make such type of decision based on their experience and knowledge [3]. The selection of a specific manufacturing process is primarily influenced by design characteristics and functional requirements. Moreover, part quality, cost, material type, and production performance should be considered when selecting the most suitable manufacturing technology [4].

Despite established human-based procedures, automated solutions are preferred when number of parts to check is large, or if human expertise is limited [5]. Although intelligent systems can ease process selection, the automation of this task has been limited by many factors and markedly the reliance on engineering drawings [6]. The available software applications used to select manufacturing processes have found relatively limited applications since they rely typically on rule-based solutions [7], as better highlighted in Section 2. This applies also if it is acknowledged that using an intelligent system can significantly shorten and improve the selection process, even without human supervision [7]. Machine learning (ML) is one of the most commonly used approaches to support manufacturing operations [8]. It can minimize the required human labelling and is more flexible than rule-based software as it can generalize over large datasets [9]. In ML-based applications, the input data can be labeled (i.e., supervised learning) and

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unlabeled (i.e., unsupervised learning) [8]. The main differences between supervised and unsupervised learning algorithms are listed below:

- Data type: supervised learning uses labeled data while unsupervised learning uses unlabeled data [10,11].
- Outcome: supervised learning predicts the output based on the input-output correlation, while unsupervised learning algorithms discover hidden patterns or structures within input data [4,8].
- Applications: supervised learning algorithms are used to predict or classify the input data while unsupervised learning algorithms are used for pattern recognition, clustering, and data exploration [9,11].

Even though supervised ML algorithms are more successful and accurate, heavy reliance on labeled data can cause problems since data labeling is time-consuming and financially demanding [12]. Overfitting is an additional problem with purely supervised learning when a small dataset is used for training [13,14]. Thus, unsupervised learning algorithms are preferred in finding patterns or clustering cases to avoid such problems [15,16]. As human-based decision-making and reasoning in manufacturing process selection still need to be explored beyond being subjective and complex to codify [17], the opportunity to investigate the capabilities of unsupervised learning arises. In addition, a chance is offered by image clustering, one of the crucial parts of unsupervised learning. While parts are typically represented graphically, image clustering is tailored to group images based on their affinities [18]. This means that part image, which displays the dimension of a part and its geometry, is a sufficient input for image clustering to work with the aim to distinguish the most suitable manufacturing process.

1.2. Considering the possibilities enabled by additive manufacturing in manufacturing process selection

In this context and with an emphasis on the suitability of manufacturing processes according to geometry factors, Additive manufacturing (AM) comes into play as an enabler of the fabrication of free-form shapes, which were previously considered impossible to fabricate at sustainable costs [19–23]. AM includes seven primary technological standards defined by ASTM/ISO 52,900 [24], namely Vat Photopolymerization, Material Jetting, Binder Jetting, Powder Bed Fusion, Material Extrusion, Directed Energy Deposition, and Sheet Lamination. AM fabricates parts from digital 3D models in a layer-by-layer or line-by-line manner, distinguishing this process from traditional manufacturing (TM) (e.g., casting, machining, forming) [25]; this is the key to AM flexibility. In the same way, AM enables the fabrication of topologically optimized parts, the reduction of the mass of components, and the decrease of unnecessary material use [26–29]. Much literature supports the tenet that AM offers geometrical complexity without additional cost and fabrication time [30,31]. On the other hand, some geometrical complexity can be achieved in TM by using injection molding (particularly for large production quantities); however, the geometrical complexity strongly affects the mold cost in this process [32].

Because of the above advantages, many companies have recently considered adopting AM technologies as an alternative manufacturing option in their product development processes [33–35]. Nevertheless, this requires the investigation of each part to decide whether it is convenient to manufacture it using AM technologies.

With the goal of shortening the time needed for decision-making in selecting AM or TM for specific parts, a recently developed unsupervised learning algorithm based on image processing [36] has been proposed by the authors and subsequently improved. Specifically, an auto-labelling algorithm based on hierarchical clustering (HC) is dealt with. This algorithm could precede the tasks performed by many decision-making support systems or algorithms available in the literature aimed to optimize manufacturing in the realm of specific groups of technologies, e.g. AM [37,38]. In most of these systems, decisions are made following a hierarchy of criteria, and, diffusedly, manufacturing technologies are chosen before process parameters, even if decisions can be reversed in an iterative fashion; a case in point is [37]. Hence, we can figure out that a multi-stage decision-making system that considers all manufacturing options (both AM and TM) could work as follows.

1. First, a pre-screening is made to determine whether parts are most suitable for AM or TM, which, as highlighted, have marked differences in terms of pros and cons. Here, much information could still be missing, and a system should be able to work with a minimal amount of information. This is the scope of the developments proposed in the current article.
2. Second, specific manufacturing technologies are chosen based on production factors (batch size, cost, etc.) and mechanical characteristics. For example, if AM is chosen in the first step, a decision should be made as regards the individual technology to be used.
3. Third, process parameters are defined to optimize the fabrication process. For instance, build orientation, which is known as an influential factor for the quality of parts fabricated through AM, should be determined along with other parameters characterizing the chosen AM technology.

As mentioned earlier, decisions made in previous steps can be challenged in subsequent steps. For instance, build orientation could influence the selection of AM processes and lead to the revision of the chosen AM technology. Yet, the above sequence of steps and criteria can be considered in a smart system, relinquishing the need to consider a plethora of factors at once.

The rationale for using geometry as a primary distinguishing factor between Additive and Traditional Manufacturing

In this research, while dealing with the first step of the above numbered list only, part geometry is the single aspect considered to classify parts. Other manufacturing process parameters and production properties, such as build orientation, material, batch size, and surface quality, are deliberately neglected. The reasons behind considering part geometry only in the preselection between TM and AM are listed below:

- Geometry is a necessary and not-substitutable piece of information to produce a part; this is normally visualized as the first information source by decision-makers.
- Freeform of part geometry is the main objective to be pursued by AM, but the literature has failed to identify a threshold of complexity, such that the advantages of AM become clear. Moreover, attempts are lacking to study how humans judge the complexity of geometry and to what extent this matters in decision-making on the choice of fabrication technologies.
- Including additional information would have led to label data and contradicted the potential benefit of using unsupervised learning. In this regard, the initial scope of the presented algorithm is to preselect parts to be possibly fabricated via AM. Many systems exist, based on supervised learning, to choose manufacturing systems and parameters based on labeled data. The developed algorithm profoundly deviates from this area of research intentionally.
- Part geometry is essential in simplifying process selection and is frequently overlooked as a primary criterion. Using part geometry only significantly simplifies the criteria involved in comparing different manufacturing processes, leading to the quick identification of the most suitable method.

1.3. Objectives

As it is typically the case for unsupervised learning algorithms, their validation takes place by comparing human designations [39] and ML-based outcomes. However, the outcomes of unsupervised learning are conveniently compared with human designations also when a ground truth cannot be defined, e.g., [40]. In the specific case, to the best of authors' knowledge, the literature has not dealt with the convergence of human experts towards manufacturing process selection, which casts doubts on the existence of a ground truth in this domain. To address this issue, a survey was developed to collect expert decisions for differentiating parts that are more suitable for AM and TM.

Consequently, within the determination of the suitability of parts to be fabricated with AM based on the part geometry, the main objectives of this paper are:

1. the introduction of an improved auto-labelling unsupervised learning algorithm to cluster parts suitable for AM and TM by considering part geometry only,
2. the investigation of the degree of agreement among experts in manufacturing process selection,
3. and the comparison of unsupervised learning clustering with human decision-making.

Only a few attempts have been made in the literature to develop unsupervised learning systems within manufacturing process selection (see Section 2). Hence, the first objective above represents an incremental step towards the development of an algorithm capable of clustering parts suitable for AM and TM, which is difficult to validate because of the debatable existence of a ground truth regarding the unique choice of a manufacturing method. Conversely, the second and third objectives are addressed in this study for the first time and represent the main elements of originality. Overall, this article represents a preliminary step into the investigation into human- and AI-based selection of manufacturing processes along with their performances and alignment.

The remainder of the article is structured as follows. A literature review is illustrated in Section 2, which covers manufacturing process selection, CAD model classification, image processing applications in manufacturing, and a comparison of human and ML performance in image classification. The methodology for generating the ML algorithm and the survey is then detailed in Section 3. The results of the ML algorithm and the survey questionnaires are presented in Sections 4 and 5 discusses the results. Finally, Section 6 draws conclusions and presents suggestions for further investigation.

2. Related work

2.1. Manufacturing process selection

Manufacturing process selection is the process of selecting the most suitable manufacturing technology that can meet specific requirements [41]. Several methodologies and intelligent systems were proposed in the literature to assist the selection of manufacturing processes; as described below, these can be categorized as process selection:

- within AM technologies,
- within TM technologies,
- across AM and TM technologies.

Many approaches have been explored in the literature to provide an effective AM process selection methodology. Multi-criteria decision-making (MCDM) has garnered much attention for AM process selection in the last two decades [42]. Several articles included different MCDM methodologies to select the best possible AM process [41,43–47,43] proposed a design-oriented AM process selection methodology that included viable material-machine combinations and practical design-oriented solutions [43,47] used an exclusive weight calculation algorithm to compare and rank different AM technologies for a specific product. A decision-maker established specific selection criteria and manufacturing constraints. AM processes were ranked based on these criteria and constraints, and the most suitable one was selected [47,48] contributed with an AM process selection method that considered material type, part complexity, part size, and some economic properties [48,49] proposed a decision-making methodology to select an AM process considering four steps: initial screening, technical evaluation, selection of AM process, and feasibility for re-evaluation and machine selection [49,50] proposed an Autoencoder and Siamese Neural Network to compare query shapes with the produced parts to achieve automatic manufacturability analysis and select a process for computer-aided process planning [50].

The most suitable TM technology is usually selected by ranking various TM methodologies using ML algorithms. For example, [6] presented a process selection methodology based on an artificial neural network (ANN) for the five most common sheet metal manufacturing processes (air bending, deep drawing, roll bending, stretch forming, and spinning) using the geometries of parts as inputs. The technology with the highest similarity was selected as the most suitable one to produce the selected part [6,51] proposed an ANN methodology to select the most suitable manufacturing technology among a sample of six candidates based on several production properties [51]. Using a neural network, [52] developed an intelligent manufacturing process recommendation system. The developed system ranked various manufacturing processes and recommended the most suitable one according to energy cost, processing time, and geometrical complexity [52]. The methodologies presented here consider specific TM technologies and predefined requirements to rank and suggest a suitable manufacturing technology.

The comparison of AM and TM technologies is investigated in the literature to a lesser extent. [53] compared injection molding with three AM technologies (fused deposition modeling, stereolithography, and selective laser sintering) by considering total production costs and lead time. Unsurprisingly, none of the investigated AM technologies could replace injection molding for high production volumes [53,54] introduced an approach to explore the importance of supply chain considerations and compare AM and TM. This article showed that AM technologies offer an environmentally friendly solution compared to TM technologies [54,55] presented an ML-based recommender system to streamline the transition of large part inventories from TM to AM. The scholars implemented the use of unsupervised learning algorithms to evaluate geometries and economical aspects of products [55].

In all these analyzed articles, efforts were made to give prominence to the positive attributes AM processes have over TM. However, these efforts did not give rise to a clear demarcation line between situations in which AM and TM processes are to be preferred. This is exacerbated by the fact that, in the available research, a manufacturing technology has been selected by considering a sample of processes defined a priori with the sole exception of [55]. Otherwise said, first literature attempts have foreseen an excessive number of constraints and lacked generalizability. This has not allowed the identification of clear criteria to recognize part characteristics leading to prefer AM and TM overall, despite the former being considered a distinct world in the manufacturing domain, or, at least, displaying unique capabilities [36,56–60]. In this context, an intelligent system operating without any constraints can represent a chance to preselect parts suitable for AM and TM before choosing the most appropriate manufacturing process belonging to either AM or TM. In order to avoid constraints, it is appropriate to develop a system purely based on unsupervised learning, which would remove the need to include any typology of information. This also makes the present contribution different from [55] where the system is fed with additional information, such as geometric features typically ascribable to AM.

2.2. CAD model classification using machine learning

One of the earliest works on CAD model classification was reported by [61] using feature extraction and a location-based descriptor to transform CAD models into numerical arrays. The scholars stored the CAD models in a library. They used a support vector machines (SVM) classifier to compare the similarities within this CAD library [61]. Ip et al. (2006) [62] proposed a supervised ML methodology that selects the most suitable manufacturing process based on shape feature information. An SVM-based ML algorithm was trained using a publicly available dataset to classify CAD models into two classes: prismatic machined and cast-then-machined [62]. In another research, Hoefer et al. (2018) [3] proposed an automated ML methodology to determine the better choice between the two classes: machining and cast-then-machining. The scholars used machining-focused manufacturability metrics based on three metric groups: aggregate geometry, facet-based orientation, and slice-based machining metrics. As mentioned before, these metrics were used to classify CAD models into two classes [3]. Manda et al. (2021) [63] developed a convolutional neural network (CNN)-based algorithm to classify CAD models. First, a CAD model dataset was generated. Then, the scholars used a weighted light field descriptor scheme to extract features from the CAD dataset. The extracted features were stored as images for each CAD model and used to develop the CNN algorithm [63]. A considerable number of CAD models are created each year for design and manufacturing purposes. The organization or classification of these models requires time and effort. As presented in this subsection, an intelligent system or an algorithm was typically used to obtain proper classifications. The available literature includes supervised learning approaches only, while the tests of unsupervised approaches were not found.

The classification of 3D CAD models carried out using supervised ML algorithms led to classification accuracies in the range of 86% to 99.96% [3,18,62,64–67]. This range can be considered as a target performance that should be reached by an unsupervised learning approach, which has otherwise the clear advantage of unneeded labeling.

2.3. The use of images in manufacturing

An image is a way of understanding, expressing, and storing knowledge as two-dimensional (2D) data. Image processing converts this knowledge to retrieve information [68]. Images are commonly used as inputs to classify geometric objects in manufacturing [69]. Image processing methods include segmentation, description, augmentation, transformation, enhancement, and recognition [68]. Table 1 shows previous examples of image processing applications in manufacturing based on image processing methods and working principles. As presented in Table 1, image processing is commonly used in manufacturing for product classification, defect detection, or shape prediction. The literature has failed so far to use image classification to select a manufacturing process. Zhan et al. [70] proposed a production monitoring methodology that used real-time images to detect the deviation of wire-feeding position in the wire arc additive manufacturing (WAAM) process. Rendall et al. [71] introduced a methodology to predict the pellet shape using a transfer learning-based deep neural network (DNN) image classifier. The pellet images were taken from a pellet manufacturer and used to train several ML algorithms: partial least squares, random forest, and DNN. The scholars stated that the DNN algorithm improved the available information for the classification task and performed best among other ML algorithms [71]. Wang et al. [72] proposed a part-sorting methodology based on CNN and image processing. The model was trained using randomly selected images of available products in a smart factory. Cameras, robotic arms, and controlling computer systems were used to detect and sort objects. The algorithm was trained using several scenarios and achieved 95% accuracy on average [72]. Consequently, image processing is commonly used to evaluate, predict, or classify part geometries in different stages of a production cycle. The main reason behind this is that images are 2D representations of geometries that require limited computational power and time. This makes images a suitable input candidate for developing an algorithm that requires low computational power and an unlabeled dataset.

A limitation that emerged in the literature, which the present paper is also concerned with, is the lack of algorithms that can process both CAD models and images, which are the two predominant formats through which parts to be manufactured are stored and exchanged.

Table 1
Examples and applications of image processing methods in manufacturing.

Source	Method	Working principle	Objective	Manufacturing Activity
[70]	Image enhancement	Feature extraction	Object detection	WAAM
[71]	Image segmentation	Feature extraction	Shape prediction	Pallet production
[72]	Image segmentation	Feature detection	Part sorting	Smart production
[73]	Image segmentation	Feature extraction	Defect classification	Welding inspection
[74]	Image augmentation	Feature recognition	Defect detection	Metal production
[75]	Image segmentation	Feature recognition	Shape classification	Metal AM
[76]	Image segmentation	Feature identification	Engineering drawing classification	Metal production

2.4. Comparison of human- and machine learning-based image differentiation

Researchers commonly evaluate the performance of proposed algorithms by means of comparisons or case studies. These include comparisons with previously established algorithms or human participants. Although these algorithms improve the field under investigation, human designations ought to be handled cautiously since human decision-making can be affected by humans' psychological state or expertise level [77]. Moreover, in some research, scholars do not report the number of human participants or their expertise level, which can bring into question the rigor of the study [78].

He at al. [79] stated that ML algorithms could reach and, sometimes, exceed human performance in image recognition tasks. The scholars also discussed and argued that ML-based visual recognition has a huge potential to reach the human level [79]. In another study, a DNN was compared to human experts to classify three different bioleaching bacterial species using microscopy images. According to the results, the DNN had 90% accuracy, outperforming human experts, who had an accuracy of 50% [80]. In another research, human learning performance and ML performance were tested by [81] with a pattern-finding experiment where three ML algorithms were trained alongside 44 human participants. The results showed similarities across all patterns for humans. In contrast, ML algorithms performed better than humans in two of the four patterns. Furthermore, the scholars pointed out that ML algorithms require more training data than humans to achieve similar results [81].

Human decision-making and intelligent systems are compared to understand and improve the predictability of intelligent systems. However, the literature failed to investigate the comparison of human decision-making and unsupervised learning algorithms in the manufacturing industry.

2.5. Research gap and original elements of the paper

One common problem regarding the use of ML algorithms to classify manufacturing processes or CAD models is the acquisition of labeled data to train supervised learning algorithms (e.g., CNN, DNN, SVM). Even though supervised learning algorithms offer high accuracy, they require large, labeled datasets for training. Over 80% of engineering tasks that contain ML algorithms require data preparation and labeling [82]. According to [83], the contribution of AI to the global economy is estimated to reach US$16 trillion by 2030, and the data labeling market will comprise a large part of it. One of the main reasons behind spending massive amounts of money on labeling is that the available datasets are usually unlabeled or poorly labeled [12]. Moreover, insufficient labeling can result in low accuracy in supervised learning as the performance depends directly on the quality of the training data [13]. This brings into question the usefulness of investigating the performances of unsupervised learning, especially when human decisions are uncertain and not codified, as in the case of the distinction of parts to be conveniently fabricated with AM and TM (see Section 2.1).

Furthermore, the literature lacks approaches that can use both 3D CAD models and images to classify parts for manufacturing process selection. Previous studies focused on comparing human decision-making with supervised learning algorithms; thus, comparing human decision-making with unsupervised learning algorithms can be seen as a novel element to be addressed.

Hence, the novelty and contributions of the paper to the field are:

1. auto clustering parts relying on only parts' geometries using unsupervised learning, thus omitting the need to acquire further information, as the former is always known prior to manufacturing process selection.
2. having the chance of using both images and 3D CAD models as input, which can be a simple and quick solution for process selection since images and CAD models of products can be easily accessible; here, it should be clarified however that the latter are processed in this paper.
3. considering only the overall distinction between parts suitable to be fabricated through AM and TM using part geometry.
4. comparing an unsupervised learning method and human decisions in the field of manufacturing process selection to explore the convergence between the two.

3. Research methodology

This section presents the methodology behind the current surveys in two sub-sections: the development of the improved HC algorithm and the development of the surveys addressed to manufacturing experts. It has to be noted that the presented algorithm is based on previous work and the corresponding freely accessible tool that were presented in [36]. The fundamental improvement of the upgraded algorithm is to distinguish the generated two clusters of parts as AM and TM (i.e., final clusters are automatically labelled), while this distinction should be made by people in the previous version [36]. As this previous version is not yet established, the authors report here the completely new algorithm without highlighting the modifications made. From here onwards, the term "auto hierarchical clustering algorithm (AHCA)" will be used to indicate the latest version used for the present study. The overall research methodology is presented in Fig. 1, including some details for each methodology and the contributions of this research.

3.1. Auto hierarchical clustering algorithm methodology

The AHCA is based on HC and image processing. The AHCA is developed in four steps, which further indicates where more information about the steps can be found:

1. Dataset collection
2. Preprocessing
3. Feature extraction
4. Clustering.

3.1.1. Dataset collection

The AHCA can work with an image dataset, a 3D CAD dataset, and a dataset containing both images and 3D CAD models. Markedly, the AHCA processes images directly, whereas 3D CAD models undergo image extraction to create a sample with consistent formats. To the scope, the SOLIDWORKS 2024 Task Scheduler was used in this research as an automated methodology to perform this extraction task; however, any CAD software that can extract images from 3D CAD models is suitable for this step. One isometric view of each part is extracted using the SOLIDWORKS 2024 Task Scheduler and used as input to the AHCA. It is recommended to have the following settings while extracting images:

- The background option is set to none,
- The shadow option is set to none.

3.1.2. Preprocessing

The extracted images are preprocessed in this step to prevent clustering from being affected by image color and size [84,85]. Hence, the subsequent steps were deemed necessary:

- Each image is converted into grayscale.
- Grayscale images are then resized into 512×512 pixels.

3.1.3. Feature extraction

Feature extraction is a method to reduce dimensionality in which a large number of pixels on an image are effectively represented to capture the significant aspects of the image [86]. The histogram of oriented gradients (HOG) is used to extract the magnitude and orientation of the edges in an image. Feature extraction is required to identify the important portions of the provided image. The extracted features are presented as a different version of the original image [87]. In this research, the highlighted features show the external geometry of the parts, including magnitude and orientation of edges. These features capture the geometric structure of the part, enabling the algorithm to identify patterns that influence AM or TM suitability. Particularly, the extracted features highlight some geometrical elements such as:

- Edge complexity: high edge density or intricate patterns can indicate parts with complex geometries better suited to AM due to the AM's capabilities.
- Surface continuity: smooth, continuous, and simple surfaces with minimal sudden changes can align with TM, which excels at the production of simple parts.
- Shape features: specific geometric characteristics, such as overhangs, lattice structures, or thin walls are indirectly captured in the gradient orientation and magnitudes.

Fig. 2 shows the HOG visualization of two parts from the input dataset. The HOG features are automatically extracted, highlighting the external geometry of each part. The images shown in Fig. 2(a) and 2(c) are converted to the image shown in Fig. 2(b) and 2(d), respectively. Then, these geometrical features (e.g., Fig. 2(b) and Fig. 2(d)) are used to highlight the differences between images; thus, the images are segregated. HOG features for each image in the input dataset are extracted in this step and used for clustering in the next step.

3.1.4. Clustering

Clustering is an unsupervised learning technique that groups/clusters data based on natural trends, relationships, patterns, or similarities without having a target variable. It is commonly used when the relationship among inputs is unknown [15,16,88]. The AHCA generates a hierarchy of clusters within the dataset based on simultaneously grouping the data [89]. This HC is used in this work to cluster the image dataset for the following reasons:

- HC provides a dendrogram that presents a visual relationship among the clusters at different levels of detail. This can provide valuable insights into the structure of the data [90]. Using HC, the user can explore the point at which any pair of parts "join together" in the tree diagram (dendrogram).

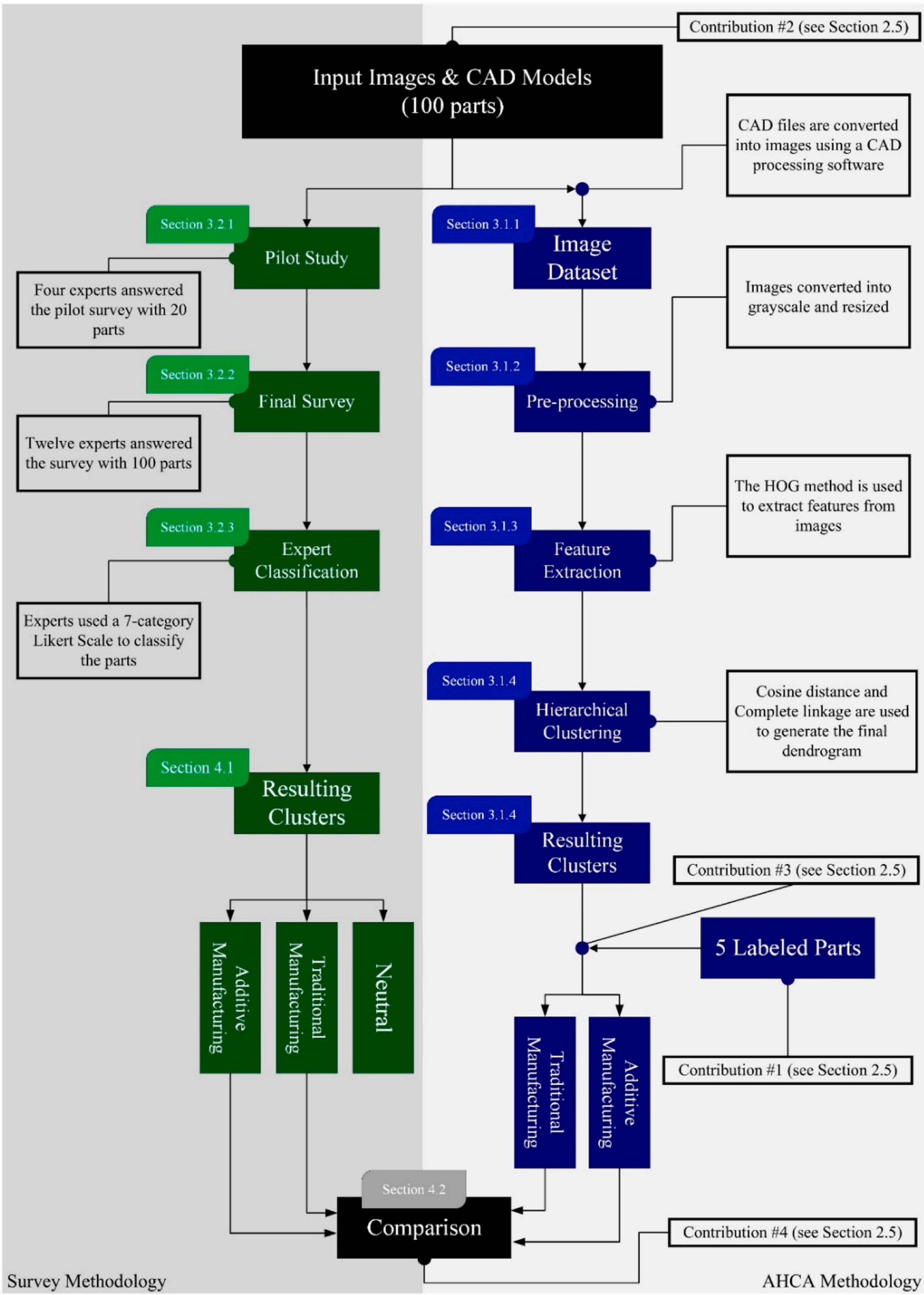


Fig. 1. Workflow of the research methodology. On the left side, the survey methodology is explained, including information regarding the pilot study, final survey, and expert evaluations. On the right side, the AHCA methodology is presented, and main contributions of the research are highlighted.

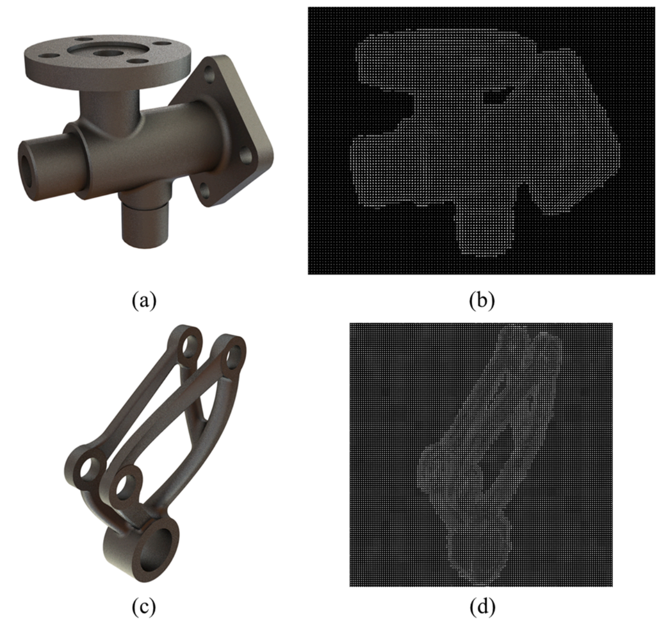


Fig. 2. (a) Part 1, (b) the HOG visualization of part 1, (c) part 2, and (d) the HOG visualization of part 2. For each image in the dataset, HOG features are generated automatically using MATLAB.

- Unlike other clustering methods, in HC, it is not necessary to predefine a cluster number [90]. This offers an advantage when the optimal number of clusters is unknown.
- HC offers a versatile approach since it can operate using various distance and linkage methods, allowing users to adapt the algorithm to specific characteristics [90].
- HOG feature extraction includes large amounts of data extracted from images; hence, HC is preferred over other unsupervised learning algorithms because it is more suitable for clustering large amounts of data [91].

The AHCA works in three steps. In the first step, the distance between each point is calculated using several methods. In the current research, the cosine distance method is selected. This method is usually employed to find similarities among images and has proven to outperform the Euclidean distance [92]. The cosine distance method is a pairwise distance calculation method that can be estimated using Eq. 1 [93].

$$\text{cosine distance} = \frac{x \cdot y}{\| x \| \cdot \| y \|} \tag{1}$$

In Eq. 1, x is the vectoral representation of the HOG pixels in Fig. 2(b) and y is the vectoral representation of the HOG pixels in Fig. 2(d).

In the second step, the linkage among the distances is found by grouping the data into a binary hierarchical tree. Several methods can be used to calculate the linkage [94]:

- Single linkage is the minimum distance between the closest members of different clusters. It is not suitable for outliers since only the closest data points are considered [94].
- Complete linkage is the maximum distance between the clusters [94].
- Centroid linkage is the distance between the centroids of the clusters [94].
- Average linkage is the average distance between each pair of members of two clusters [94].

The complete linkage is chosen in the current research since it is the most commonly used method for image clustering. It produces compact, spherical clusters and is more robust to noise and fluctuations within the dataset [95].

In the final step, five AM-labelled parts are introduced to label the two resulting clusters as AM and TM. These five parts were deliberately selected as designed for AM and fabricated via AM according to ASTM/ISO 52,900 [24]. This is the major novelty of the AHCA from an implementation viewpoint, a new approach that sets it apart from the traditional HC algorithm, as the final clusters are automatically labelled. The AHCA needs to be rerun whenever a new part or dataset is introduced as input.

In order to evaluate and validate the quality of clustering, the Silhouette coefficient is calculated. It is a validation method that measures the similarity of a data point to its cluster ranging from -1 to 1, which is calculated using Eq. 2 [96]. A score above 0.5 indicates that the clusters are well-separated and defined, while a score closer to 1 is desired [97–99]. Even though there are other methods to validate clustering, (e.g., k-means clustering [55]), in this research, the Silhouette evaluation is used in line with [97,98] to validate clustering.

$$\mathrm{S(i)} = \frac{b(f) - a(f)}{\max(a(f), b(f))} \tag{2}$$

where S(i) is the Silhouette coefficient, a(f) is the average distance between the data point f and all other data points in the same cluster, and b(f) is the average distance between the data point f and all other data points in the nearest different cluster.

The clustering methodology behind AHCA utilizes the HOG vectors to differentiate parts based on their geometrical features (see Section 3.1.3 for details). The suitability to AM or TM is assessed through AHCA, which groups parts with similar geometrical profiles, while AHCA itself does not explicitly encode thresholds for manufacturability (due to the nature of unsupervised learning).

In this research, all calculations and algorithms were developed using MATLAB 2024b version software and run on AMD Ryzen 7 3700×3.60 GHz CPU, ASUS NVIDIA GeForce RTX 2080 SUPER GPU, and 32 GB RAM. The AHCA is presented in eleven steps as shown in Table 2, and is stored in a GitHub repository[1] where a user guide is also present to explain its use.

3.2. Survey development

Surveys are one of the most common data-analysis methods in the manufacturing industry [100]. Many recent studies in the manufacturing industry have included a questionnaire or survey to map and predict the current state of production methods and strategies [101,102]. The survey development procedure involves designing, distributing, and collecting the required information from a target audience. In this context, the authors created and circulated an online survey, which comprised two online surveys, among manufacturing experts from industry and academia, as made apparent in the following. The scope of the survey was to evaluate experts' opinions on the suitability of parts to be conveniently fabricated with AM and TM. The details of the pilot study, the final survey, and the distribution of the survey to the manufacturing experts are explained in the following sections.

3.2.1. Pilot study

A pilot survey with twenty parts to be classified was distributed among four manufacturing experts to evaluate the clarity of the task and determine the tolerable number of parts to be processed. The participants were asked to classify the parts using a seven-point Likert scale. The parts were presented with an image and an accessible link to a 3D CAD model of the part in the survey (the participants can use the link "See the CAD model" presented below each image, as shown in Fig. 3). A screenshot from the survey is shown in Fig. 3, in which each product was

[1] GitHub repository.

Table 2
The AHCA algorithm.

Algorithm: AHCA
1: Initialization: Generate an image database
2: ***For*** each image in the database
3: Convert into grayscale
4: Resize
5: Extract features
6: ***end***
7: Store extracted features in a matrix
8: Calculate distance using Eq. 1
9: Calculate linkage
10: Import 5 AM-labeled parts
11: Present results as Figs. 4(a), 4(b), and 5

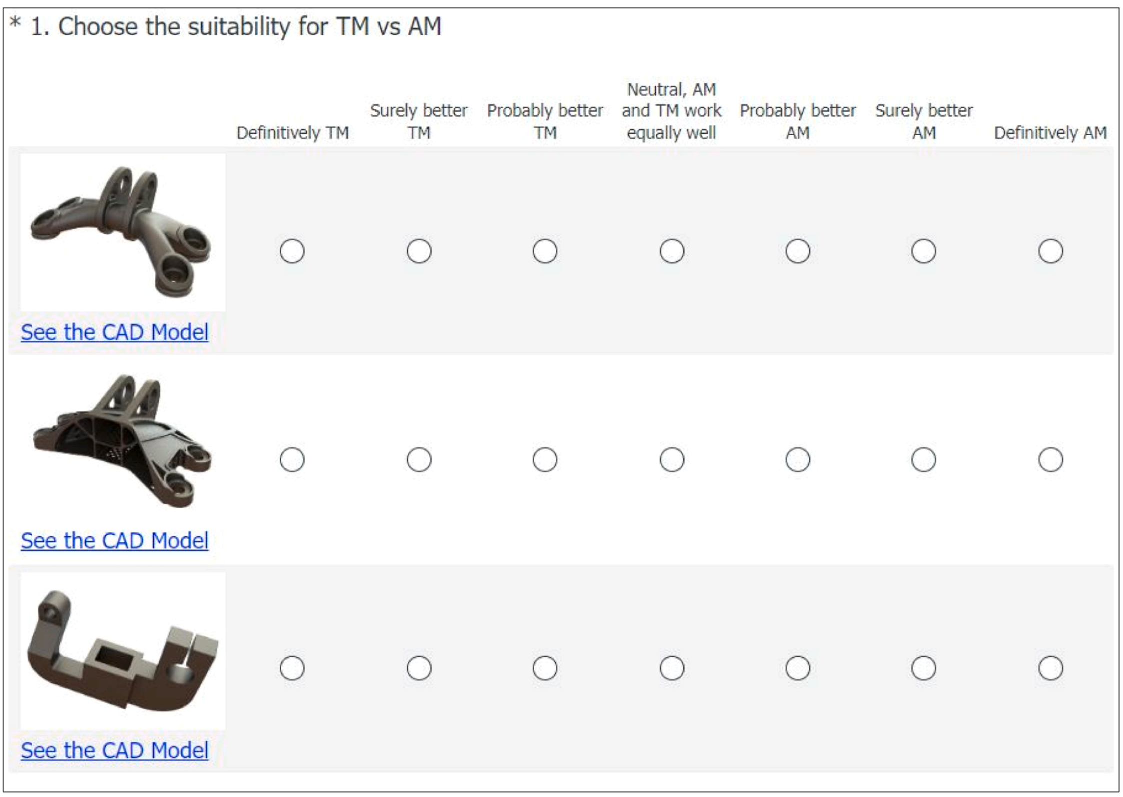


Fig. 3. Example question and the seven-point Likert-scale used in the pilot and final surveys. Each part was represented with an image and a link to its CAD model.

ranked between one (TM definitively more convenient) and seven (AM definitively more convenient). As there are typically pros and cons of using different technologies, the use of a scale is intended to give the possibility to rate each part with intermediate scores. The authors intended to investigate one hundred parts in a final version of the survey, considering that typical unsupervised learning algorithms in the engineering field process few dozens of elements [103–106]. Hence, the participants were asked to evaluate the feasibility of classifying one hundred products with a simple yes or no question considering their experience with the pilot study. Based on participants' feedback, the following actions were taken to improve the clarity of the task:

- Examples of TM and AM technologies were included in the final version,
- A scenario was presented at the beginning of the survey to justify the reasonableness of opting for AM and TM based on geometries only,
- Five parts were included on each survey page to visualize the rating scale clearly.

In brief, the pilot study evaluated the clarity of task conditions, the rating scale, and the number of parts that can be processed in a reasonable time. A scenario was formulated to introduce the survey because some participants in the pilot study asked for clarifications regarding the need to consider geometries only in their evaluation. In particular, the participants were asked to provide a reference or a context where their evaluation could make sense. The scenario is presented in subsection 3.2.2, where the final survey is discussed. According to the pilot study results, fifty was considered the maximum number of parts an expert can classify in a reasonable time. Hence, two surveys with fifty questions were eventually designed and circulated.

3.2.2. Final survey

The task to be performed by the participants remained relatively the same with respect to the pilot study. Specifically, the participants were asked to judge the suitability of each part to be fabricated with TM versus AM technologies using the same seven-point Likert scale, as shown in Fig. 3. This scale was used in the final survey since no adverse comments were received in the pilot study in this respect. Each part was presented with an image and a link to the 3D CAD model of the part to replicate the information available to the AHCA. The product images were presented in the survey, and the participants had to click on the "See the CAD model" link below each image to visualize the CAD model of a product that was stored in an online database. The participants were asked to consider the following scenario while making their decisions:

"Imagine you are a manufacturing company that has so far used Traditional Manufacturing (TM) technologies to produce parts. You are evaluating the chance to switch from TM to AM for some of the parts you produce. You want to pre-select parts that could potentially fit AM better based only on the geometries of the parts (the presented images in this case). At present, you have no further information about quality requirements, sample size, mechanical properties, etc. Otherwise said, even if all these factors are clearly influential, your evaluation should be based on the presented geometry only."

The proposed scenario reflects the condition of some companies that want to exploit acquired AM production capabilities and evaluate which parts or products are most suitable for the newly introduced AM technology, even without any redesign. As highlighted in the scenario above, the participants were asked to evaluate each part using only the image or the CAD model without considering any other properties.

3.2.3. *Distribution of the surveys*

Potential respondents were identified by involving industrialists and academicians who work on manufacturing technologies. The survey was disseminated by first contacting some of the experts in the field via email and advertising ongoing research at two international conferences on engineering and design, respectively. The eligible participants should have fulfilled the following requirements:

- Being affiliated with a university, a research center, or a manufacturing company.
- Having at least five years of experience in manufacturing technologies including AM.

3.2.4. *Conducting the surveys*

The survey was conducted from May to August 2023. Twelve manufacturing experts with more than five years of experience in the field participated in the study. Table 3 shows some details of the experts who answered the surveys. It was made possible to available experts to answer both surveys. A preview of the surveys is available in the following links: Survey A[2] and Survey B.[3]

Table 3
Details of experts who participated in the survey.

Expert #	Workplace	Years of Experience	Industry	Country
Expert 1	Academia	15	Manufacturing	Italy
Expert 2	Academia	8	Manufacturing	Italy
Expert 3	Academia	7	Manufacturing	Spain
Expert 4	Academia	35	Design & Manufacturing	Finland
Expert 5	Academia	5	Manufacturing	Italy
Expert 6	Academia	15	Manufacturing	Finland
Expert 7	Academia	7	Design & Manufacturing	UK
Expert 8	Academia	8	Manufacturing	Croatia
Expert 9	Industry	8	Manufacturing	Finland
Expert 10	Academia	7.5	Manufacturing	Sweden
Expert 11	Academia	6	Manufacturing	Italy
Expert 12	Industry	7	Manufacturing	Turkey

3.2.5. *Level of agreement among survey participants*

The overall agreement among the experts can be evaluated using an inter-rater reliability coefficient, namely Krippendorff's alpha. It is a measurement model that evaluates the agreement among the participants, observers, or raters [107]. It is particularly suitable when data is not continuous, and evaluators are multiple. It can be calculated using the method provided in [108].

3.2.6. *Evaluating survey results*

The median of the evaluations on the convenience of using AM attributed to each part was calculated, leading to the categories reported in Table 4. In brief, parts were classified into those more suitable to TM and AM according to the median of the evaluations received through the seven-point Likert scale.

4. Case study and results

The one hundred 3D CAD models[4] (recognized as machine parts and final products) to test the AHCA were randomly collected from freely accessible online databases (e.g., GrabCAD). The overall one hundred parts correspond to inputs of the AHCA.

4.1. *Survey results*

Some responses were excluded from the analysis due to the limited variability in the evaluations (i.e., the evaluations were the same for all parts). In the end, six evaluations for each sample were suitable for consideration. This led to classifying 46% of the parts as more suitable for fabrication using TM technologies, while 40% were found to be more appropriate for AM. Having reported a median value of 4 (neutral), the remaining 14% were classified as equally fit for both AM and TM. The Krippendorff's alpha for the provided evaluations was calculated and reported as 0.0823, which, according to [109], states poor agreement among the participating experts.

4.2. *AHCA results*

The AHCA generates three figures that can be used to determine AM and TM clusters:

- Cluster 1 – Traditional Manufacturing (See Fig. 4(a))
- Cluster 2 – Additive Manufacturing (See Fig. 4(b))
- The dendrogram (See Fig. 5)

The AHCA labeled Fig. 4(a) as Cluster 1 – Traditional Manufacturing while Fig. 4(b) as Cluster 2 – Additive Manufacturing. Hence, Figs 4(a) and 4(b) represent parts more suitable for fabrication with TM and AM, respectively, based on the AHCA results. Fig. 5 shows results of AHCA as a dendrogram with an analysis of clustering quality at different levels (2,

Table 4
Categories of designations of parts based on the median of experts' evaluations.

Median	Category
<4	TM
4	Neutral
>4	AM

[2] Survey A Link.
[3] Survey B Link.
[4] CAD Models.

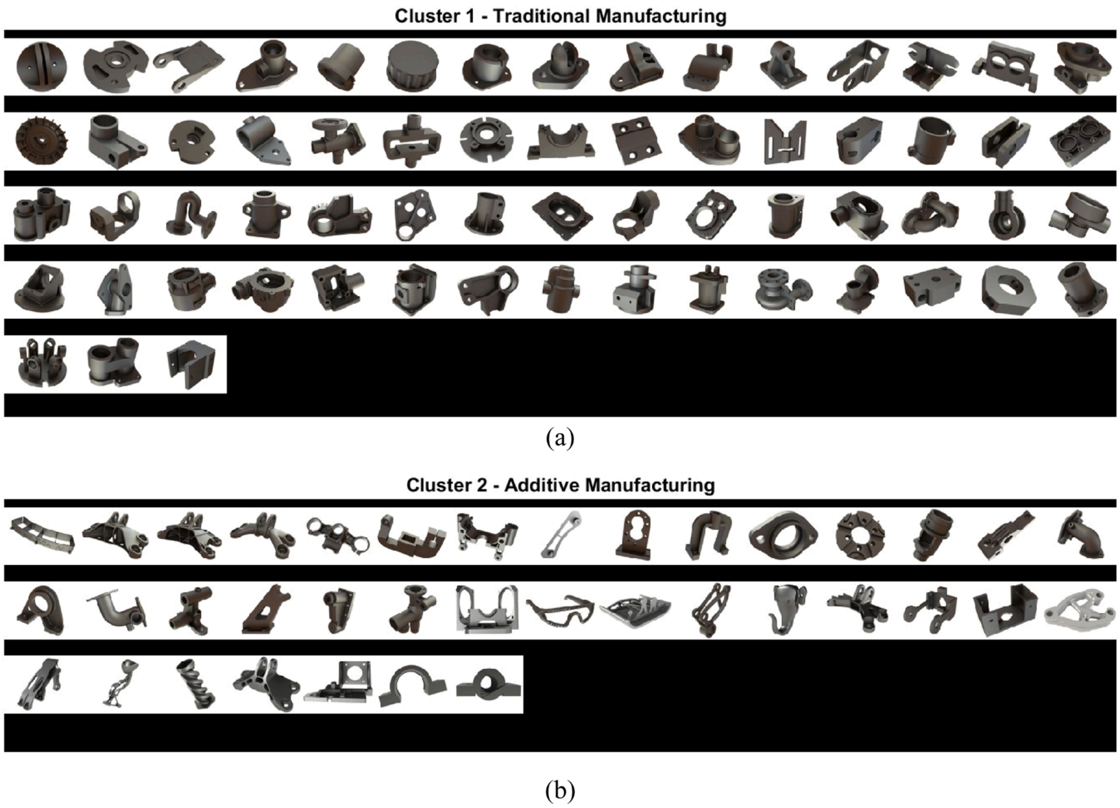


Fig. 4. Results of the AHCA (a) Cluster 1 – Traditional manufacturing (63 parts) and (b) Cluster 2 – Additive Manufacturing (37 parts).

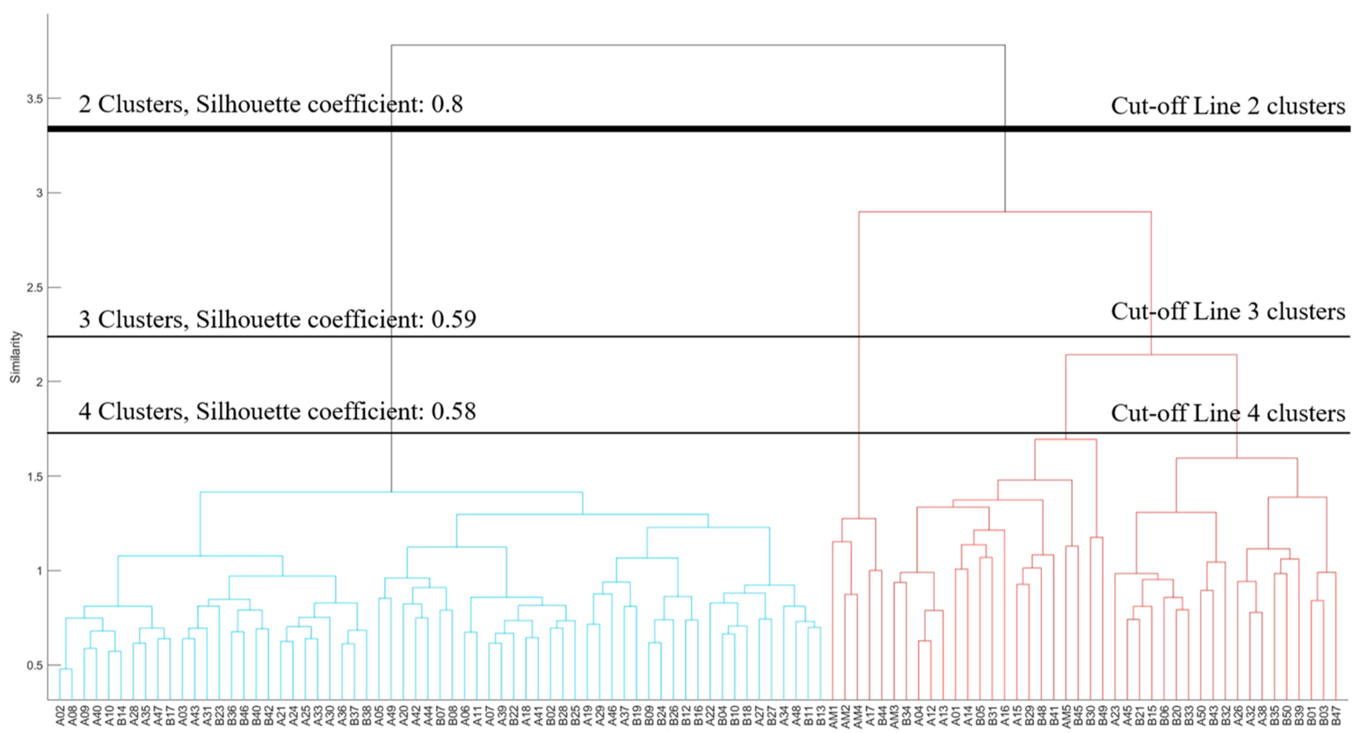


Fig. 5. Resulting dendrogram for the AHCA with 100 parts. Based on the Silhouette coefficients, the Cut-off Line with 2 clusters was selected and two clusters were achieved. Light blue lines represent the parts in Cluster 1 – TM in Fig. 4(a) and red lines represent the parts in Cluster 2 – AM in Fig. 4(b).

3, and 4 clusters). The validation of the clustering quality of each cut-off line was evaluated using Silhouette coefficient (see Section 3.1.4 for details), resulting in 0.8 for 2 clusters, 0.59 for 3 clusters, and 0.58 for 4 clusters. As a higher value indicates better clustering, the final decision for this research was to use two clusters. Hence, in this research, the dendrogram was cut into two clusters, where Cluster 1 – TM is presented with a light blue color, whereas the red lines represent Cluster 2 – AM. In Fig. 5, the x-axis represents the 100 input parts, while the y-axis shows the distance between the clusters (i.e., the dissimilarity among generated clusters).

To make the processes comparable in terms of inputs, it is worth noting that:

- the AHCA clusters each part based on the HOG features extracted from each image, which is obtained from a 3D CAD model used as initial input;
- experts evaluate each part using the same extracted part images and can access, if needed, the corresponding 3D CAD file, which is linked in the survey.

By considering the 86 parts that did not fall in the Neutral category based on the median of experts' evaluations, a convergence of 78% between human decisions and the results of the AHCA emerged. Otherwise said, for 78% of parts, the cluster assigned by the AHCA coincides with the class assigned based on the median of experts' designation as shown in Fig. 6. Convergence between the AHCA and experts is then found for all parts clustered as AM (TM) through ML and classified as AM (TM) by the survey participants because their evaluations have a median greater (smaller) than 4.

The variance of the evaluations for each part was subsequently calculated using the function "var" in MS Excel, revealing a range between 0.17 and 4.4. Fig. 6 shows the convergence among experts and results of AHCA, including a confusion matrix. The set of evaluated parts was arbitrarily subdivided into three sub-categories according to the values of variance, as shown in Fig. 6:

1. Variance values below 1 were considered as an indication of a noteworthy alignment among survey participants. 21 parts were in this category.
2. Conversely, variance values above 2.5 were associated with a considerable divergence among the participants, denoting a low level of agreement. 16 parts were in this category.
3. Variance values between 1 and 2.5. 49 parts fall in this category.

For each sub-category in Fig. 6, a confusion matrix is presented to show the comparison between experts and AHCA results. Further investigation was conducted on the two sub-samples (1st and 2nd categories) denoting high (1st category) and low (2nd category) convergence among manufacturing experts. The AHCA results exhibited a notable pattern, aligning with experts when their agreement is high (the parts that fall into the 1st category) and substantially misaligning when the level of agreement is low (the parts that fall into the 2nd category). The share of agreement between the AHCA results and the median of experts' ratings was 90% for the former (1st category) and 63% for the latter (2nd category). The parts that fall into the 3rd category had 72% convergence rate with AHCA.

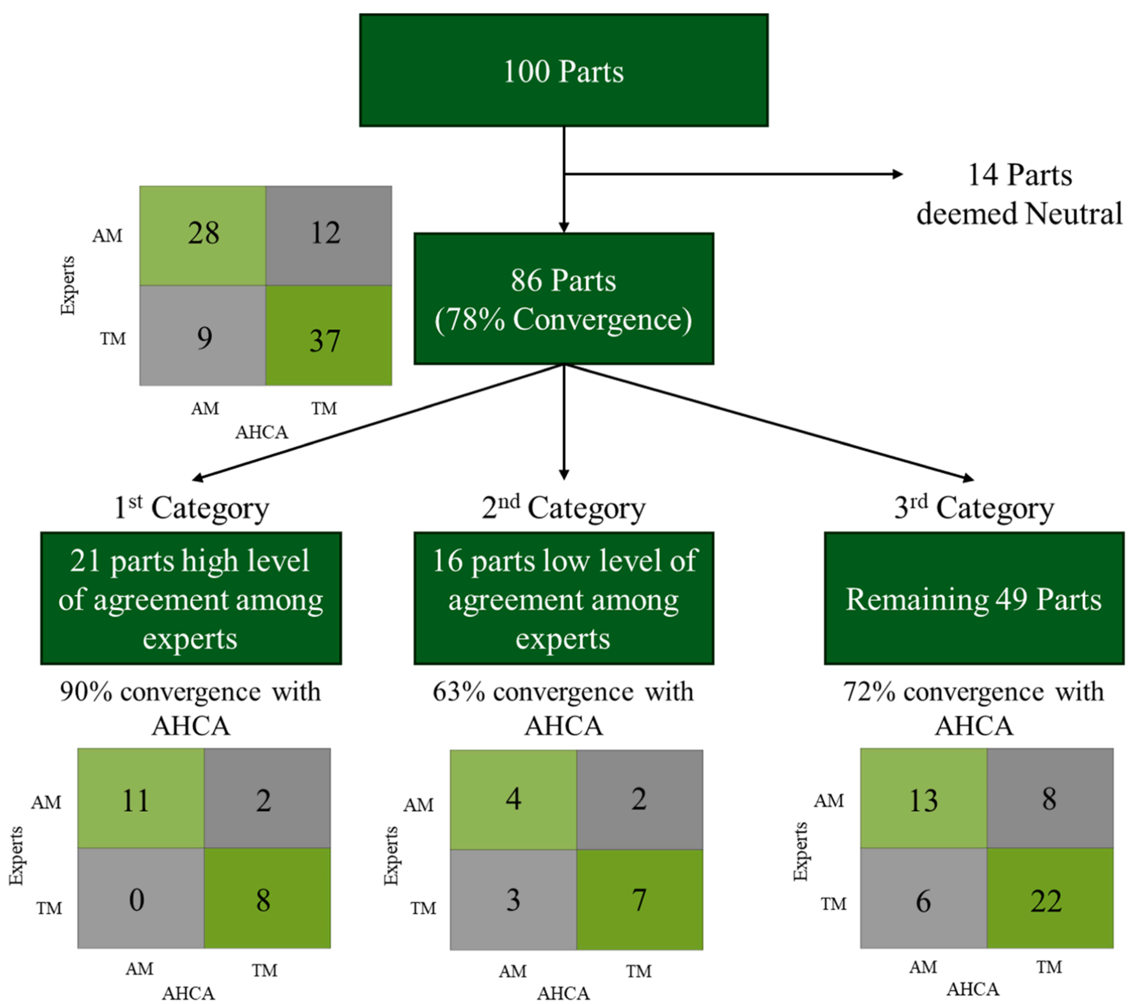
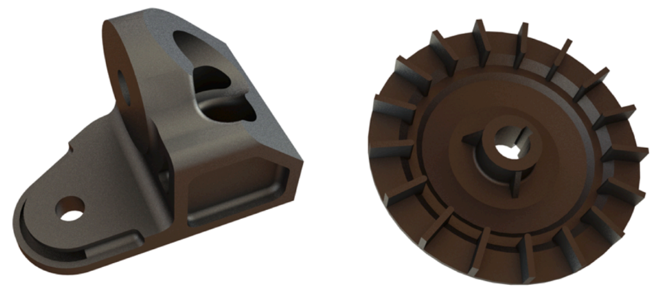


Fig. 6. Analysis of the survey to highlight the convergence between the experts' designations and AHCA, including a confusion matrix comparing the median of experts' designations and AHCA clustering results (light green cells in confusion matrixes show the agreement with human experts, grey cells in confusion matrixes show disagreement with human experts).

Fig. 7 shows some of the parts with a low level of agreement among experts (2nd category in Fig. 6) and where the AHCA shows misalignments. The authors identify the following geometrical features as shared geometric characteristics in parts for which misalignments took place:

- The parts contain protrusions.
- Many cavities are present on the parts.
- The parts contain portions with varying thickness.
- The parts contain a few curved surfaces.

Fig. 8 shows parts that were categorized differently by the AHCA and the experts despite their high level of agreement (1st category in Fig. 6). The AHCA rated the parts presented in Fig. 8 as more suitable for TM, while the experts found these parts more suitable for AM. However, the median of expert decisions for the part in Fig. 8(a) was 4.5, while this was 5 for the part in Fig. 8(b). Considering the 7-point Likert scale used in the surveys, both parts were then overall classified as "Probably better AM". In other words, the experts were uncertain that these parts would be only suitable for AM. Thus, the inconsistency between the expert decisions and the AHCA can be acceptable for these specific parts as expert opinions do not lead to affirm that they can be manufactured with AM only.



(a) (b)

Fig. 8. Parts clustered differently by the AHCA and the experts and that, at the same time, exhibit substantial agreement among experts (1st category from Fig. 6).

5. Discussion

From a research standpoint, the primary focus of the paper was to develop an auto clustering algorithm and to compare the outcomes of AM/TM differentiation performed by the AHCA and human experts through a survey. Three major results are worth stressing here:

- The convergence among expert evaluators was almost nil, when the randomly selected one hundred parts are considered.
- The convergence between the median of expert evaluations and the outputs of the AHCA was 78%, considering 86 parts, which were not designated as "Neutral" by the pool of experts.
- The convergence between expert evaluations and the AHCA was 90% for parts characterized by a high level of expert agreement (1st category, see Fig. 6 for more details). Hence, the outcomes of the AHCA are more questionable when the designation of the most suitable fabrication technology is very challenging for experts too.

With respect to the first bullet, the results confirm some tenets of the paper regarding the limited understanding of the links between designs and corresponding manufacturing processes. On one hand, the human processes oriented to select a manufacturing process for specific geometries present no regularities. As such, these reasoning processes cannot be replicated in intelligent systems. While selection based on sample size, mechanical characteristics, and accuracy is codified and repeatable, which could explain the performance of some available research, the geometric peculiarities of parts might be ignored in the selection process even if they are a plainly relevant factor. On the other hand, expectations were not met that the complexity of geometries resulted in a discriminating factor in the choice of AM and TM unless complexity was evaluated differently by the involved experts. Otherwise said, experts failed to identify those elements that make designs specific for exploiting claimed AM's unique capabilities. This aspect can represent a concern for research, especially within the Design for Additive Manufacturing field, where cases in point for the use of AM as a fabrication technology [19,110] are presented. However, based on the very limited convergence of expert evaluation (2nd and 3rd categories in Fig. 6), the characteristics of parts designed for AM are either insufficiently known or still too vague to draw a demarcation line between AM and TM. This aspect will be examined in the authors' future work.

As for the degree of convergence between humans and the AHCA, this data can be compared to the performance of supervised systems presented in Section 2.2 only if a ground truth is established. Here, it is possible to consider the existence of a ground truth for those cases where the most convenient manufacturing process is reasonably identified, hence for parts that fall into the 1st category (see Fig. 6). In these instances, geometry clearly favors either AM or TM, and, as such, geometry itself can be considered an objective basis for manufacturing process selection. However, for the 2nd and the 3rd categories (see Fig. 6), as the level of agreement among experts is lower, part geometry alone is insufficient to select the most suitable manufacturing process. In other words, for these categories, additional information is required to make a certain decision.

The 90% convergence achieved for parts belonging to the 1st category shows that the performance of ACHA is comparable with data-demanding supervised learning systems, as shown in Fig. 9, markedly the first five columns of the histogram.

Thus, focusing exclusively on geometry has the potential to provide valuable results for the preselection of the most suitable manufacturing process. Nevertheless, while this approach sheds light on the role of part geometry in process selection, the authors acknowledge that other factors (intentionally excluded in this study) remain essential to a fully informed manufacturing process selection. If we assume that, as in other studies, human designations are the target results to be achieved by ML systems, the 78% convergence can be considered a positive outcome since it was achieved

- without data labelling or specific instruction on how to perform the AHCA,
- without considering factors (e.g., mechanical, quality-related, and cost) that have proven to be highly discriminating in the selection of manufacturing processes, as underlined above.

As already highlighted, it is recognized that other factors beyond part

Fig. 7. Parts clustered differently by the AHCA and the experts and that, at the same time, exhibit low agreement among experts (2nd category from Fig. 6).

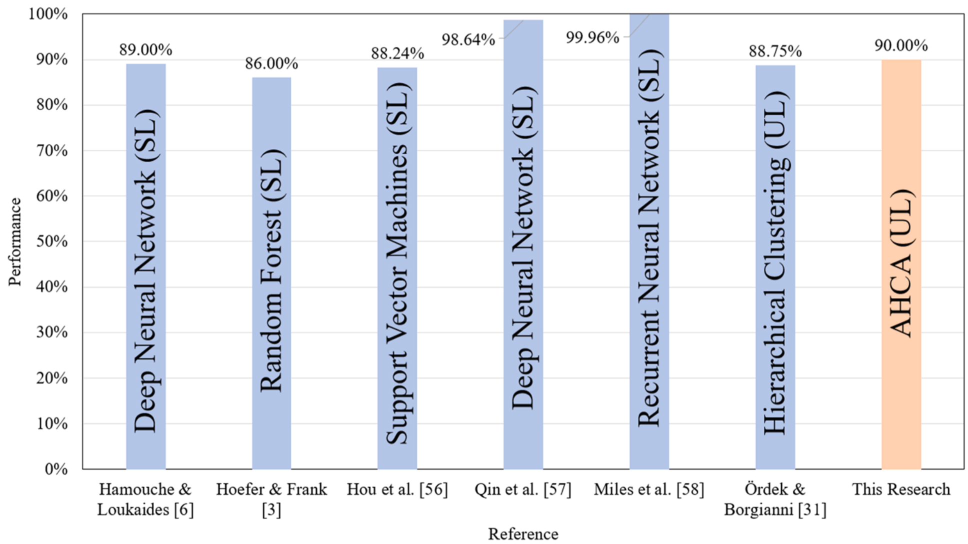


Fig. 9. The comparison of AHCA performance with supervised machine learning methods found in the literature [3,6,36,64–66].

geometry affect manufacturing process selection. For example, injection molding or investment casting is most suitable when high batch numbers and relatively complex geometries are involved. To this end, the clusters made by the AHCA can be helpful even when specific parameters such as material, mechanical properties, surface finish, or batch number make AM disadvantageous. In these cases, the parts classified in the AM cluster could be considered candidates for casting. Even though the AHCA was developed to exploit the design freedom enabled by AM, it can also be useful for parts intended to be fabricated using TM technologies. It is also important to note that AHCA is intended as a support tool for human decision-making rather than an alternative. A part can be suitable for fabrication with multiple manufacturing processes since a clear demarcation line between manufacturing conditions that lead to selecting a process over another does not exist. In this respect, the role envisioned for the AHCA is to enhance decision-making in the manufacturing process selection.

Alongside the positive points achieved in the current research, it is essential to acknowledge certain limitations that unavoidably affect the scope and generalizability of the findings. The identified limitations of the AHCA are listed below:

- The AHCA has to be re-run when new data is introduced.
- The AHCA uses images to cluster the parts, which implies converting input files into images, potentially limiting its applicability. In this research, 3D CAD models were converted into images using CAD processing software. However, it can be noted that modern CAD software have programmatic access to the CAD kernel via an API, e.g., NXOpen from Siemens NX, which can be used to obtain the required snapshots of the CAD model in an automated manner and systems with such capabilities (knowledge-based engineering systems) are expected to be ubiquitous in the future [111].
- One isometric view for each product is used in this research for clustering the parts. This can result in omitting some features. However, introducing only one image per part decreases the processing time and results in a quick and relatively accurate solution.
- HOG features can be affected by shadows and background graphics, making it difficult to distinguish the important sections from the surrounding noise [112]. Hence, the proposed methodology pre-processes images to remove background noise and shadows.
- HOG is not suitable for low-resolution images [112]. Thus, high-resolution images were used to develop the proposed algorithm.

6. Conclusions and future work

A contribution of this paper is an algorithm (i.e., AHCA) that automatically clusters parts to be fabricated using AM or TM based on geometries alone. Here, "part geometries" refers to the external shapes and structures of the parts. The two overall domains of TM and AM are considered initially, supported by literature claims about the uniqueness of AM capabilities as far as geometric characteristics are concerned. The AHCA works through unsupervised learning, thus eliminating the need to label data. As mentioned, the AHCA has demonstrated the possibility of supporting the preselection of parts that could be suitably produced with AM technologies. Moreover, the proposed methodology can support the identification of parts suitable for being conveniently fabricated with AM in a flexible, simple, and inexpensive manner while, at the same time, eliminating human effort for data labeling. With regards to the speed of operations, the AHCA can perform the preselection of 100 parts in a few seconds, while experts spent 11 min on average to evaluate the suitability of AM and TM for 50 parts. Therefore, this algorithm is suitable for manufacturing companies that produce a large variety of parts and intend to reorient their production capabilities. This applies especially to those companies that have introduced AM technologies, but these are poorly exploited for the fabrication of final parts, which is not infrequent based on the authors' experience. The AHCA achieved the following results by considering part geometry only and using an unlabeled dataset:

- The comparison between the AHCA's results and the median of experts' decisions showed 78% convergence for 86 parts, while the experts' decisions had a relatively poor agreement.
- The AHCA results had 90% convergence with experts' designations with high levels of agreement (see Fig. 6).
- The resulting Silhouette score for the AHCA is 0.8 for 2 clusters, which shows that the determined clusters are well-constructed and separated.

Hence, the AHCA showed great potential for supporting the decision-making process in differentiating parts suitable for AM or TM with a compatible convergence rate.

The development of the AHCA and the comparison with human designations were the main objectives of this research, as clearly reported in Section 2.5. However, further steps are needed to achieve the goal of the unsupervised selection of manufacturing processes. Future work will be devoted to improving the AHCA methodology and understanding the reasons behind the selections made by the manufacturing experts. Experts' reasoning processes could be used to switch from a purely unsupervised system to an algorithm based on reinforcement learning. In this regard, an investigation will be conducted to understand the reasons and criteria behind human decision-making in selecting a manufacturing process. Based on this data, it will be possible, for example, to verify whether some aspects beyond geometry should be considered with priority in manufacturing process selection. By enriching the algorithm with other pieces of information to cluster parts suitable for AM or TM, the authors will be able to verify whether these pieces of information can actually give rise to substantial benefits in terms of AHCA performances. Otherwise said, advantages can be assessed following the consideration from the very beginning of properties and parameters related to

- production, e.g., batch size, which could be critical to orient the choice towards TM;
- mechanical and quality performances, e.g., taking into account surface finish could lead to accept AM technologies, but introduce a warning to limit the selection to those AM processes compatible with subsequent machining;
- process parameters, e.g., the impossibility to find a convenient build orientation could lead to exclude AM also for relatively complex parts, or at least, introduce a warning to limit the selection to those AM processes possibly working without supports.

Another future work will be about generating a point cloud to store multiple views or sections of each part. Beyond providing more details of the parts, this could alleviate the neglection of build orientation as a critical process parameter when it comes to AM.

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CRediT authorship contribution statement

Baris Ördek: Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation. **Eric Coatanea:** Writing – review & editing, Resources, Investigation, Formal analysis, Conceptualization. **Yuri Borgianni:** Writing – review & editing, Validation, Supervision, Project administration, Methodology, Investigation, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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