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ORIGINAL ARTICLE

Experts' and novices' views on the use of additive manufacturing for the fabrication of parts based on their geometry

Baris Ördek[1,2] · **Yuri Borgianni**[2]

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Abstract

Although complex designs are acknowledged to be more suitable for fabrication with additive manufacturing, there is no formalized definition of what makes a geometry sufficiently complex and accordingly appropriate for additive manufacturing. This lack of a standardized definition represents a challenge for engineers and designers. In this context, the objective of this study is to evaluate the role of part geometry in manufacturing decisions and to understand the criteria influencing the selection of a manufacturing process. This research used semi-structured interviews with 11 experts and a survey with 37 novices to gather data. Through ten questions, participants were requested to evaluate ten shapes of parts without further information and speculate on their suitability for additive manufacturing. It emerged that some of the experts stressed batch volume, material, part size, mechanical properties, cost, and material waste as fundamental criteria for selecting a manufacturing process, while novices did not consider material waste and cost as critical aspects. Part geometry was overall given secondary importance unless the part included specific features such as thin walls, lattice structures, and optimized topologies, where the selection leant towards additive manufacturing for both experts and novices. The latter preferred additive manufacturing (70% of the answers) more frequently than the former (54%). Overall, this study highlights the differences in decision-making criteria between experience levels and underlines the need for a formalized framework to evaluate geometric suitability for AM.

✉ Baris Ördek
baris.ordek@unibg.it; barisordek@gmail.com

[1] Department of Management, Information and Production Engineering, University of Bergamo, via Marconi 5, Dalmine (BG) 24044, Italy

[2] Faculty of Engineering, Free University of Bozen-Bolzano, Via Bruno Buozzi 1, Bolzano 39100, Italy

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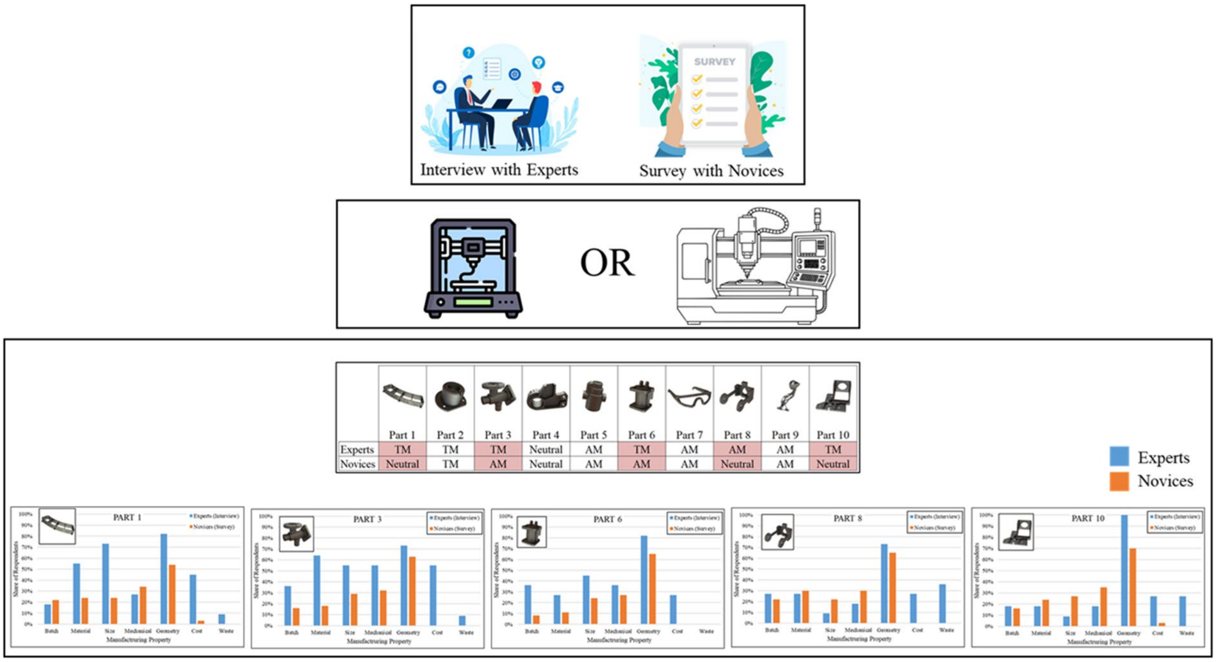
Graphical abstract



Keywords Design for additive manufacturing · Geometric complexity · Manufacturing process selection · Semi-structured interview · Experts · Novices

1 Introduction

Additive Manufacturing (AM), or 3D Printing, is a general term used for various manufacturing processes that work by adding material layer-by-layer. AM offers design freedom and is considered well-suited for the fabrication of complex parts [1]. This is primarily due to the fact that AM processes offer the unique ability to control the position and amount of material deposited, jetted or processed. As a result, AM is often associated with lightweight design, conventionally achieved through topology optimization (TO) and the integration of lattice structures, which help maintain mechanical integrity while minimizing material use [2–4].

While freeform geometries are a peculiar trait of parts fabricated with AM, other manufacturing properties are to be considered before selecting a manufacturing process; markedly, the use of AM or other traditional manufacturing (TM) technologies should be evaluated first [5]. Typically, the selection of manufacturing technology is based on human expertise and knowledge. However, newly established and constantly improving technologies can affect human understanding of the most suitable process; here, the level of expertise and the acquisition of fresh knowledge play an essential role. Comparing the views of experts and novices in the fields of manufacturing and design is often deemed useful for gaining diverse perspectives and improving decision-making.

As stressed in Sect. 2, a significant research gap remains in understanding how decision-making varies between experts and novices, particularly regarding the role of part geometry in manufacturing process selection. In this context, the paper provides a novel contribution by directly comparing experts' and novices' decision-making in selecting a manufacturing process alongside understanding the influence of part geometry. More specifically, the objectives of this research are to:

1. Identify the differences in the decision-making process of experts and novices regarding manufacturing process selection, with an emphasis on the preference of AM over TM and vice versa,
2. Assess the influence of certain geometrical characteristics/features on manufacturing process selection,
3. Determine the geometrical changes that are supposed to make a part more suitable for AM.

Section 2 is an overview of the existing literature regarding the comparison of fabrication with AM and TM, the relation between Design for AM (DfAM) and part geometry and comparing experts and novices in their approach to DfAM. Following the literature analysis, the research gaps and the justification of the above objectives are highlighted in the same section. Section 3 describes the overall methodology of the paper. The main results are presented in Sect. 4, where the comparison between the decision-making of experts and novices is focused on. In Sect. 5, a detailed discussion of the results is reported. Finally, in Sect. 6, conclusions are drawn, and future research directions are indicated.

2 Background

2.1 Comparing fabrication with additive and traditional manufacturing

The possibility of substituting TM with AM for the fabrication of parts is affected by multiple factors the literature has identified. Among the most prominent factors, the following are worth citing:

- Production costs and time [6–8].
- Part geometry [8–12].
- Production volume and customizability [13].
- Environmental impacts and life cycle assessment (LCA) [14–16].

Several studies compared AM processes with TM processes, such as injection molding [6] and machining [7, 8], by considering the factors mentioned above. Injection molding was found superior for medium and high production volumes, while AM was advantageous for low-volume, highly customized and complex parts. Specifically, combining selective laser melting with TO resulted in weight and cost reduction for aerospace components [7]. Additionally, feasibility frameworks [8], hierarchical clustering [9], and geometry analyses [10] were proposed to evaluate AM suitability. Environmental investigation through LCA showed that sustainability of a process was highly dependent on machine utilization [14], while, according to [15], laser-engineered net shaping was identified as more resource-efficient compared to CNC machining for specific applications. Table 1 shows the summary of prominent articles that compare AM and TM considering the aforementioned factors.

This subsection shows that the literature evidences a large variety of aspects for evaluating and comparing AM and TM, beyond some contrasting conclusions and many efforts made to ease selection. While papers highlight the advantages and disadvantages of using AM instead of TM, there is a critical gap related to generalizability, as past studies suffer from the consideration of a few case studies. Furthermore, another significant gap is the absence of investigations into human perspective and reasoning in manufacturing process selection, particularly in industrial scenarios characterized by data scarcity and lack of information. Addressing these gaps is crucial because mapping of human reasoning could be relevant especially in view of its replication by artificial agents, which could compensate for the scarcity of available experts [17]. The overall goal of replicating human reasoning in manufacturing process selection is the thrust of the present research, which can be seen as a first step in this direction thanks to the fulfilment of the three objectives declared.

2.2 Design for additive manufacturing and part geometry

The decision to use AM is sometimes made before the final characteristics of parts have been decided. In this context, DfAM includes methods and principles that support designing parts to be favorably built through one or more AM processes [18]. DfAM methods and tools that affect the geometry of a part include TO, lattice structure design, generative design, and design heuristics for AM, among others.

TO reorganizes material within a specified design boundary, considering physical and geometrical constraints [19]. While TO can easily configure the optimization solver and visualize the shape evaluation [20], optimized designs often require post-processing and solver configuration [21, 22]. Methods such as length scale control [23–25] and machine learning (ML) [26] have addressed challenges like thin walls and large overhangs, respectively.

Lattice structures are significantly used for weight reduction [27], material efficiency [28], obtaining specific mechanical properties [29], thermal management [30], enhancing functional integrity [31], improving energy absorption [32], and bio-inspired designs [33]. The final mechanical performance highly depends on the lattice geometry of the unit cell and loading conditions [34], exhibiting their adoptability across diverse applications.

Table 1 Comparison of AM and TM from selected studies

Source	Additive Manufacturing	Traditional Manufacturing
[6]	AM has more advantages in low-volume production due to potentially lower costs and shorter lead times	TM is more suitable for medium and high volumes due to lower per-unit cost and efficiency
[7]	When combined with topology optimization, it significantly reduces cost and weight for titanium parts	Machining was found to be less effective in reducing cost and weight for complex aerospace components
[8]	AM is more suitable for complex and highly customized parts for low production volumes	TM is more efficient for high-volume, standardized parts
[10]	AM was found to be more efficient in using resources during production of standard spur gears	TM consumed more resources compared to AM in producing standard spur gears

Generative design includes computational tools to optimize geometry specifically for manufacturing processes [35, 36] as applied in several CAD software programs. According to [37], it is not possible to fabricate generative designs without AM since they are too complex for TM processes.

Design Heuristics (DHs) are attempts to formalize information derived from tacit knowledge and the designer's experience [38]. Bespoke DHs for AM were developed by [39, 40], which can be seen as the most popular technique within DfAM. Moreover, contrary to the above tools that have been developed independently from AM and DfAM, the DH for AM can be seen as a first general methodology as they include a variety of strategies to design and redesign for AM. The DHs were initially applied through experimental research that focused on novice designers (students). According to [39], firstly experimented DH for AM showed promising results and allowed novice designers to deliver satisfactory design results. After the initial application of DHs in DfAM, DHs were used in different settings and design phases. For example [41], included DHs in a one-day workshop to evaluate the usage of DHs in design with experienced designers. DHs were also implemented to redesign AM products and were found to be successful. A further experiment with novice designers showed that using cards depicting DH for AM highly improved quality and creativity in redesign for AM [42, 43]. The conventional DH for AM encompasses eight categories: part consolidation, customization, convey information, materials, material distribution, embed/enclose, lightweight, and reconfiguration [43]. Accordingly, the application of most DHs would lead to geometric changes, similarly to TO, generative design and the application of lattice structures. This confirms the close relationship between shape and suitability to AM.

The methodologies described and DfAM, in general, suggest ways to wield the potential and unique capabilities of AM, but they do not provide criteria for the suitability of designs for AM. A critical research gap stands in the fact that these approaches do not offer explicit criteria or verification methods to conclusively determine whether a final design is definitely suitable for AM. Otherwise said, while most methods comprise guidelines to redesign or manipulate geometries to make them more suitable for AM, they do not verify that the final design is definitely suitable for AM. This fundamental research gap in the field of DfAM is one of the foci of this article, as made evident through objective 3 in Sect. 1.

2.3 Comparing experts and novices in design for additive manufacturing

As observed in regard to DHs for AM, DfAM research often involves the focus on experts and novices.

The comparison between the two groups has been the core of numerous design studies, with a particular emphasis on design experts and design students [44]. A key distinction between experts and novices lies in the depth, organization, and accessibility of their knowledge domain, as well as their ability to apply this knowledge in problem-solving efficiently [45]. The literature indicates that experts use solution-focused approaches to generate a quick initial solution, unlike problem-focused approaches [46, 47]. A core objective of these studies is the creation of interdisciplinary teams of experts and novices, supposed to improve communication during educational design projects.

In [48], the ideation performance of experts and novices was compared after presenting DfAM-based design principles. The results of this study highlighted that experts generated higher-quality ideas compared to novices when DfAM principles were presented [48] [47]. aimed to understand the influence of using different ways to present DfAM rules on designers' ability to use them by comparing experts and novices. Designers were asked to use four rules for fused deposition modelling to design overhangs, accessible support structures, planar surfaces, and part sizes. Each design rule was given in four formats: text only, text with industry examples, text with illustrations, and text with 3D printed examples. The comparison between experts and novices showed that experts generated more novel designs [47].

As AM is a relatively new addition to the education system [49], decision-making in manufacturing process selection emerges as an appropriate area to be investigated through the different lenses of experts and novices. The existing literature does not explicitly address or systematically compare how experts and novices differ in their reasoning and decision-making regarding manufacturing process selection. In other words, this lack of comparative understanding between experts' and novices' approaches generates a significant gap. Addressing this gap, as stated in the first objective of this research, is essential for developing balanced, effective, and adaptable educational methods for manufacturing process selection in engineering and design education.

3 Methodology

The methodology employed in this study to pursue its objectives includes a semi-structured interview and a survey. This section explains these approaches alongside the data analysis used to extract information. The overall research roadmap is presented in Fig. 1, where reference subsections for the various methodological steps are indicated.

Figure 2 shows the ten parts included in this study. The survey and the interview swiveled on the analysis of these parts, notably on the determination of the most suitable technology for their fabrication.

Parts 7 and 9 were selected intentionally to better target objective 2 (See Sect. 1) while parts 2 and 10 were deliberately selected from TM-ed parts to accomplish objective 3. Part 7 contains lattice structures, and Part 9 has been topologically optimized; hence, both parts were specifically designed for AM. The other parts were selected from a set of parts that were disagreed on in a previous study conducted by the authors [10]. Each part was presented with an image and accessible link to its 3D CAD model in the interview and the survey.

3.1 Semi-structured interview

Semi-structured interviews are used to collect detailed information about participants' insights into a specific subject area [50]. They are a valuable tool in design research for capturing detailed and rich information. Applications of this methodology in design research include user experience design [51], product design [52], process selection [53], and service design [54, 55], among others. To fulfill the objectives of this research, expert knowledge was collected using a semi-structured interview. The interview methodology is explained in three steps in the following subsections.

3.1.1 Interviewee selection

The eligible interviewees were identified considering experts from industry and academia with expected knowledge in AM. The experts were invited to the interview via an email in which they were asked to share their availability for the study. Eleven experts agreed to participate in the interview following the authors' invitation. Some details of these experts are provided in Table 2.

3.1.2 Planning and generating open-ended questions

The semi-structured interview was developed to understand the experts' reasoning behind selecting a manufacturing process. In the planning phase, a pilot interview was conducted to evaluate.

- the clarity of the questions.
- the relevance and pertinence of the questions in relation to the objectives of the study.
- the interview duration.

These evaluations led to the final version of the questions; markedly, the following improvements were made:

- Question I (in Table 3) was included in the interview to observe how an expert would describe a geometry.
- Question II (in Table 3) was included in the interview to verify the eligibility of experts for the interview.

The interview eventually comprised ten questions, as shown in Table 3. Each question was included considering at least one of the objectives presented in Sect. 1 or acquiring contextual information (indicated with roman numerals in Table 3).

Questions 1 to 8 were asked also in the survey while Questions I and II were only asked in the interview. In Question 1, the survey and interview participants were asked to rank each part using a seven-point Likert scale, as in Table 4. Each part was ranked between one (TM is more convenient) and seven (AM is more convenient), while four meant neutrality, i.e., the part was found equally suitable for AM and TM. The participants were given the opportunity to rate a part with intermediate scores since there are typically pros and cons of using different technologies.

The interview questions were asked following a branching logic, which follows:

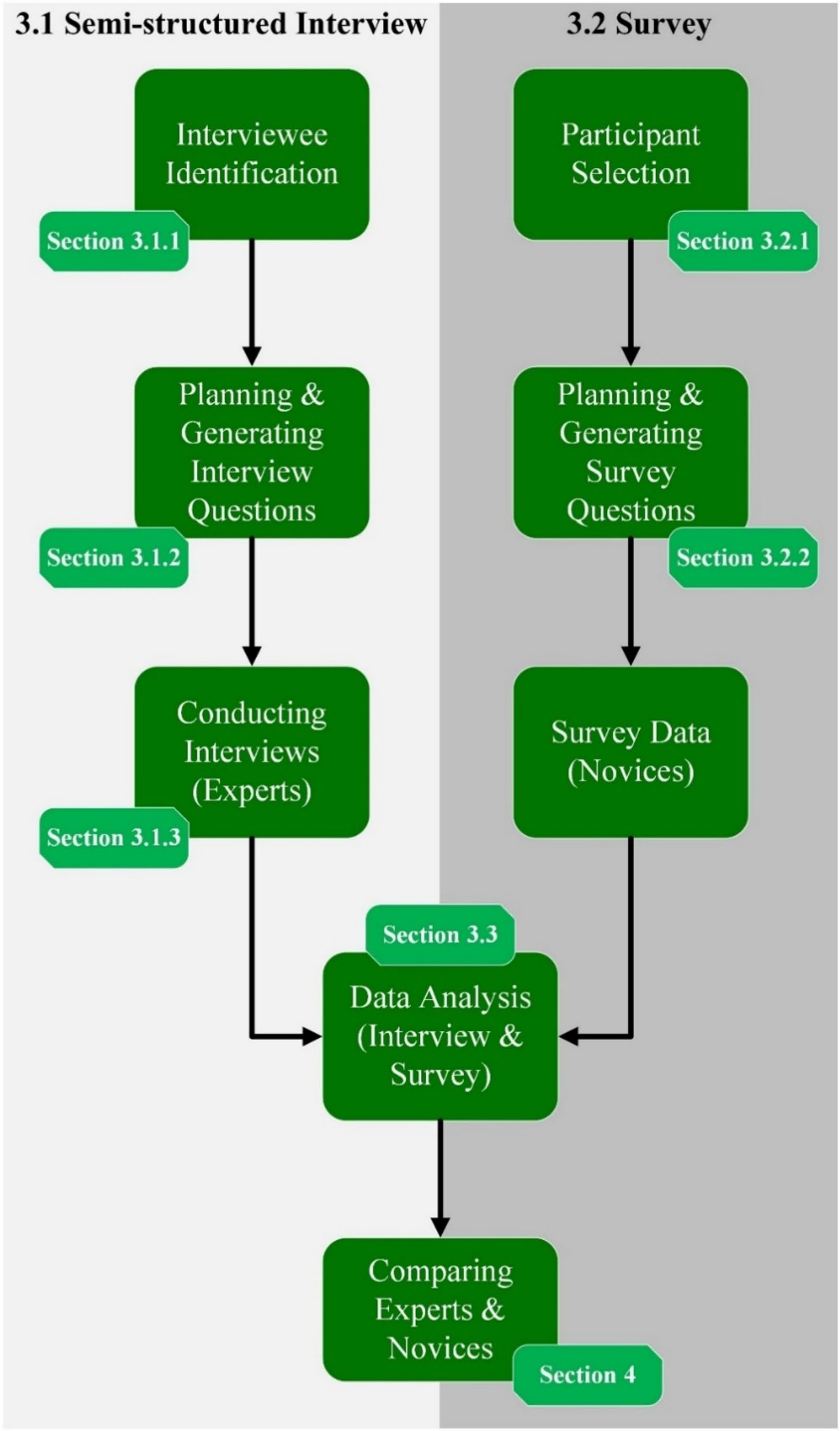
- If a participant found a part more suitable for TM (answer to Question 1 in Table 3), the interviewer asked the Questions 4, 5, and 6 in Table 3.
- If the part was found more suitable for AM (answer to Question 1 in Table 3), then Questions 7 and 8 in Table 3 were asked next.
- The participants were redirected to the next part if a part was found suitable for both technologies.

For the sake of clarity, Questions 1, 2, and 3 were asked to all participants irrespective of previous answers.

Additional questions were included in the interviews. Questions I was asked to understand the relationship between part geometry description and manufacturing processes. Question II was asked to verify the suitability and experience of experts who agreed to be interviewed. Based on answers, all interviewees were considered eligible.

3.1.3 Conducting the interviews

The interviews were conducted by the same person (the first author of this paper) from January to April 2024 with the support of MS PowerPoint and the MS Teams platform. Each interview lasted around 30 min and was recorded using MS Teams to utilize the transcript function. Before the interview, each interviewee was asked to sign a recording consent form that included a general introduction, the purpose of the recording, confidentiality, storage of the recorded data, and withdrawal from the interview. Most of



3.1 Semi-structured Interview
3.2 Survey
Interviewee Identification
Section 3.1.1
Participant Selection
Section 3.2.1
Planning & Generating Interview Questions
Section 3.1.2
Planning & Generating Survey Questions
Section 3.2.2
Conducting Interviews (Experts)
Section 3.1.3
Survey Data (Novices)
Section 3.3
Data Analysis (Interview & Survey)
Comparing Experts & Novices
Section 4

Fig. 1 Overall research methodology. Details for each step are given in the linked subsection

the interviews were carried out in English. The transcripts of the interviews conducted in other languages were subjected to automatic translation into English with MS Word.

Survey Methodology.

Surveys, one of the most commonly used data collection methods in the production industry [56], are a practical and efficient tool in design research. They are employed to gather information on design requirements [57], material selection [58], user experience [59], design prototyping [60], cost analysis [61], environmental impacts [62], and quality assurance [63], among others. Within this framework, the authors created and distributed an online survey to collect data from novices. This approach was chosen over repeating the interviews with the available cohort of novices, as the latter would be impractical due to time constraints.

3.1.4 Survey participants

The survey was conducted at the Tampere University in Finland with 37 Master of Science students (i.e., novices) in February 2024 during a course specifically addressed to AM.

3.1.5 Survey questions

The survey was developed through the software application Survey Monkey. In order to compare the decisions of experts and novices, Questions 1 to 8 (See Table 3) were included in the survey considering the ten parts presented in Fig. 2. The parts were presented in the survey with an image and a link to the corresponding CAD model replicating the interviews. While Questions 2 and 3 (from Table 3) were open-ended in the interview, some recurring experts' answers were merged to formulate a multiple-choice question where the participants were asked to select at least one option (see Fig. 3).

The survey included an introduction page that stated the objective and motivation of the questionnaire, as well as instructions on how to complete the survey. The survey foresaw the same branching mechanism of the semi-structured interviews (see Sect. 3.1.2 for details).

Data Analysis.

Text mining was used to analyze and extract information from the interview answers [64], markedly with regard to information needed to pursue objectives 2 and 3. An overview of the used text mining methodology is presented in this subsection to provide some details about data collection, preprocessing, and feature extraction.

Specifically, the text data from the semi-structured interviews were analyzed using Orange software [65], where the flowchart designed to generate the keyword frequency analysis is shown in Fig. 4. The Orange software is selected to perform this analysis because it is open-source software, many libraries are available, and it has a user-friendly interface [66].

3.1.6 Data collection

As mentioned before, the interview data were collected using the MS Teams platform, and the transcripts for each interview were generated automatically. Each transcript was divided into subsections that contained answers to each question.

3.1.7 Preprocessing

The interviews were noisy and included some unnecessary information. The authors cleared unnecessary information by going through the transcripts and recordings for each interview. The interview data was converted into a corpus to be prepared for the analysis. The preprocess Text function of Orange software was utilized. The text was transformed into lowercase format, and articles, prepositions, pronouns, conjunctions, punctuation, numerical values, modal verbs, adverbs, and interjections were removed. The text was tokenized and normalized.

3.1.8 Feature extraction and result visualization

The preprocessed text was used to generate the word-frequency matrix to highlight the frequency of specific terms. These matrices are used to extract information from the interview results considering the open-ended questions. Subsequently, after getting the frequency of terms, the authors selected those that were deemed relevant in relation to the objectives of this research (see Sect. 4 for details).

4 Results

This section illustrates the main outcomes of this research. The results presented in this section regarding expert evaluations include the outcomes of the text analysis presented in Sect. 3.3.

Seven manufacturing properties emerged as the most influential factors for selecting a manufacturing process: material, part size, part geometry, batch number, mechanical properties, production cost, and material waste. These properties were identified using the transcripts from all eleven interviews by analyzing the results obtained from the Orange software. Table 5 shows the term frequency for all eleven transcripts and all parts, as well as the number of experts

Fig. 2 Parts used in the survey and the semi-structured interview

Table 2 Details of interviewed experts

Expert #	Field	Experience in AM	Discipline	Country
Expert 1	Industry	6 years	Manufacturing	Turkey
Expert 2	Industry	5 years	Manufacturing	Turkey
Expert 3	Industry	7 years	Manufacturing	Turkey
Expert 4	Academia	35 years	Design & Manufacturing	Finland
Expert 5	Academia	5 years	Desing	Finland
Expert 6	Academia	8 years	Manufacturing	Finland
Expert 7	Academia	6 years	Design	UK
Expert 8	Academia	6 years	Design	Sweden
Expert 9	Academia	8 years	Manufacturing	Finland
Expert 10	Academia	7.5 years	Manufacturing	Finland
Expert 11	Academia	6 years	Manufacturing	Finland

and novices who recognized these properties as essential for the manufacturing process selection (i.e., answers to questions 2 and 3). The frequency of terms reported in Table 5 refers to those occurrences where the term is meant as a means for manufacturing process selection. Hence, for the sake of clarity, it was checked whether any term possibly representing a manufacturing property was actually mentioned by experts to denote a decision-making criterion in the context of their answer. For example, the frequency of the word "material", meant as a manufacturing property relevant to process selection, was 81; 9 experts and 10 novices mentioned this term while answering questions 2 and 3 for at least one part. The following quote is taken from one of the transcripts to show that "material" is used specifically as a manufacturing property to answer question 3 for part 2:

> *…based on the application we could think about having a different **material** on the inside of the cylinder and that would impact whether I would go with traditional or additive manufacturing because with additive it is easier to add a new layer of coating on the inside surface….*

The following subsections are articulated according to the objectives declared in the introduction section.

4.1 Experts vs. novices in manufacturing process selection

The results of the survey and interview were compared to discover possible differences between novices' and experts' decision-making by considering answers to Question 1 (see Table 3). The strength of correlation was calculated with Krippendorff's Alpha for experts' and novices' answers to Question 1. The emerged correlation value is 0.156 for experts and 0.138 for novices where these values show poor agreement levels [67] for both cohorts. By separately considering the 11 experts' and 37 novices' answers to Question 1, the median was calculated to provide a final classification for the separate cohorts of experts and novices for each part following the criteria presented in Table 6. The differences in the final classification for experts and novices are highlighted in Fig. 5.

Experts and novices overall classified parts 1, 3, 6, 8, and 10 differently. A further analysis was conducted to understand the reasons behind the differences in experts' and novices' decisions. To do so, answers to Questions 2 and 3 were analyzed considering the seven manufacturing properties that emerged from the text analysis of expert interviews, as explained at the beginning of Sect. 4. Table 7 shows the answers to Questions 2 and 3 for parts 1, 3, 6, 8, and 10. For each of these products, the top three properties selected by the majority of experts and novices are shown in bold text in Table 7. The following points were the outcomes of the comparison between experts and novices:

- The majority of experts indicated that seven manufacturing properties influence the choice of the manufacturing process for at least one part, while very few novices

Table 3 Semi-structured interview questions, their motivation, corresponding objectives, and answer type

#	Question	Motivation	Objective	Answer Type	Included in the Survey?
I.	Could you please describe the presented geometry?	Evaluating how an expert would describe a geometry	-	Open-ended	No
II.	Could you please state how long you have been working with Additive Manufacturing or Manufacturing in general?	Verifying the eligibility and experience	-	Open-ended	No
1.	Is this part more suitable for AM or TM?	Evaluating part suitability based on geometry (AM vs. TM)	1	Likert Scale	Yes
2.	Could you please specify some aspects you considered while making your selection?	Evaluating the aspects considered while answering Question 1.	2	Open-ended	Yes
3.	Which factors beyond geometry would you consider with priority to establish the best technological process to fabricate this part?	Further investigation of manufacturing aspects considered to answer Question 1.	2	Open-ended	Yes
4.	What would you change in this geometry to make it (more) suitable for AM?	Evaluating the possible geometrical changes to make the presented part more suitable for AM.	3	Open-ended	Yes
5.	Do you have in mind any specific TM process or technology to fabricate this part?	Evaluating expert's process selection (among TM processes).	2	Open-ended	Yes
6.	Do you think that this part was intentionally designed for TM?	Evaluating if only the presented geometry is sufficient to decide this.	2 & 3	Yes/No	Yes
7.	Do you have in mind any specific AM process or technology to fabricate this part?	Evaluating expert's process selection (among AM processes).	2	Open-ended	Yes
8.	Do you think that this part was intentionally designed for AM?	Evaluating if only the presented geometry is sufficient to decide this.	2 & 3	Yes/No	Yes

Table 4 Seven-category likert scale that was used to answer question 1 in the survey and the interview

Definitely TM	Surely Better TM	Probably Better TM	Neutral, AM & TM Work Equally Well	Probably Better AM	Surely Better AM	Definitely AM
1	2	3	4	5	6	7

* 2. Please specify some aspects you considered while making your selection. (Select the most suitable options (s) provided below.)

- ☐ Presumed Material of the product
- ☐ Presumed Size of the product
- ☐ Presumed Batch number (Number of parts to be manufactured)
- ☐ Only the shown geometry is sufficient to select a process
- ☐ Presumed Mechanical properties (e.g., tensile strength, hardness, stiffness, ductility, etc.)
- ☐ Other (please specify)

Fig. 3 Illustrative question from the survey

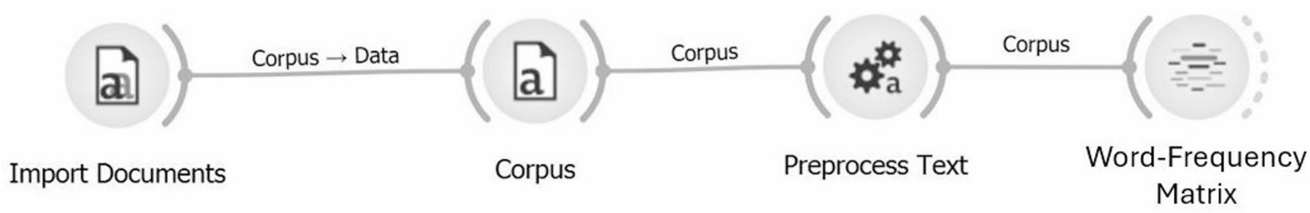


Fig. 4 Orange software flowchart for generating term-frequency matrix

Table 5 Frequency of each manufacturing property, the number of experts and novices who considered them while answering questions 2 and 3. *the word mechanical refers to mechanical properties of a part

Manufacturing Property	Frequency	Number of experts	Number of novices
Material	81	9	10
Size	43	9	10
Geometry	38	11	22
Batch	27	6	9
Mechanical*	20	8	14
Cost	16	8	2
Waste	13	7	0

Table 6 Classes of designations based on answers to question 1

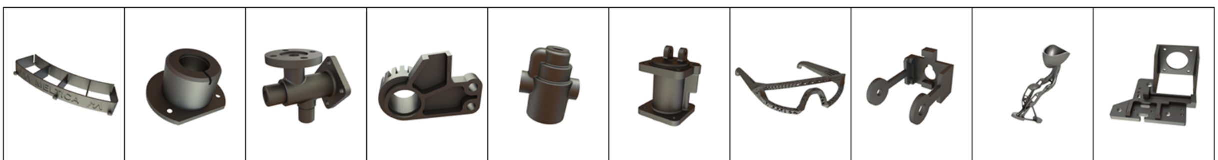
Median	Classification
<4	TM
4	Neutral
>4	AM

considered production cost and material waste. This could be one of the main reasons behind the different classifications by experts and novices.

- Novices tend to select AM more than experts, as shown in Fig. 5. A possible explanation is that novices consider AM as the most straightforward option since, according to [68], novices lean to select the easiest and most attainable option.
- Experts and novices generally prioritized part geometry, material, and mechanical properties to determine if a part is suitable to be fabricated with AM or TM.

In conclusion, as regards objective 1, novices tend to select AM more frequently than experts. In half of the cases, the manufacturing process selection made by samples of experts and novices was uneven, which stresses the importance of considering experience in this domain of research.

Overall, within the sample of products analyzed, experts' designation overall leant towards TM. 54% of experts' decisions resulted as AM-oriented. On the other hand, 70% of



	Part 1	Part 2	Part 3	Part 4	Part 5	Part 6	Part 7	Part 8	Part 9	Part 10
Experts	TM	TM	TM	Neutral	AM	TM	AM	AM	AM	TM
Novices	Neutral	TM	AM	Neutral	AM	AM	AM	Neutral	AM	Neutral

Fig. 5 Comparison of manufacturing process selection of experts and novices in process selection (based on answers to Question 1 in Table 2.). TM: Traditional manufacturing. AM: Additive manufacturing. Neutral: AM and TM work equally well

Table 7 Answers to questions 2 and 3 by experts and novices for those parts in which disagreement on the most suitable manufacturing technology arose

Data Type	Batch	Material	Size	Mechanical	Geometry	Cost	Waste	PART #
Experts (Interview)	18%	**55%**	**73%**	27%	**82%**	45%	9%	PART 1
Novices (Survey)	22%	**24%**	**24%**	**34%**	**54%**	3%	0%	
Experts (Interview)	36%	**64%**	**55%**	**55%**	**73%**	**55%**	9%	PART 3
Novices (Survey)	16%	18%	**29%**	**32%**	**63%**	0%	0%	
Experts (Interview)	**36%**	27%	**45%**	**36%**	**82%**	27%	0%	PART 6
Novices (Survey)	8%	11%	**24%**	**27%**	**65%**	0%	0%	
Experts (Interview)	**27%**	**27%**	9%	18%	**73%**	**27%**	36%	PART 8
Novices (Survey)	**22%**	**30%**	**22%**	**30%**	**65%**	0%	0%	
Experts (Interview)	18%	18%	9%	18%	**100%**	**27%**	**27%**	PART 10
Novices (Survey)	16%	**24%**	**27%**	**35%**	**70%**	3%	0%	

novices are oriented towards AM, showing a stronger preference for AM. This might be due to the fact that novices tend to reflect enthusiasm for newer technologies, as will be discussed in Sect. 5.

The responses are used to perform a statistical analysis to evaluate the significance of the role of expertise in AM vs. selections. The statistical model chosen is the ordered logistic regression since the inquired independent variable (AM suitability) is measured on a Likert scale. The following results are obtained:

- The regression with all data confirms that novices tend to evaluate the suitability of AM for the parts investigated at a higher level than experts; however, the effect of experience ($p = 0.171$) is not significant, if $p < 0.05$ is used as a rule of thumb.
- When the regression is considered for parts individually, the same pattern applies for parts 1, 2, 3, 4, 5, 6, 8, and 9. While for parts 7 and 10, the following are achieved:
  - For Part 7, experts provided slightly higher scores, but the difference is clearly statistically insignificant.
  - For Part 10, novices' designations leant more towards AM, and the effect of expertise is statistically significant ($p = 0.027$).

4.2 Influence of specific geometries on manufacturing process selection

The presence of certain geometrical features, such as lattice structures, TO, and surface finish, highly influenced the decisions of the two groups.

Figure 6 shows the manufacturing properties considered by experts and novices to decide whether Part 7 is more suitable to be fabricated using AM or TM. The experts and novices designated these parts suitable for fabrication via AM as expected (see Fig. 5). As it is clearly inferable from Fig. 6, part geometry highly affected the decision-making process since the part contained specific features that lead to preferring AM. Some experts also stated that properties such as material, size, or mechanical properties can influence the decision to select a specific AM process rather than deciding the suitability to AM or TM.

These results fully support that the presence of features ascribable to the use of TO and to lattice structures are recognized as a sufficient motivation to select AM to manufacture parts. In other terms, the presence of these features overturns the priority commonly assigned to production and quality characteristics and makes part geometry the most influential factor in manufacturing process selection [69, 70]. In this regard, pertaining to objective 2, it can be concluded that not only does the literature claim that TO and lattice structures are key methods for DfAM, but also is the application of these methods overwhelmingly acknowledged as tightly connected to AM. This makes AM a universally recognized fabrication technology to produce parts that have undergone TO and/or the introduction of lattice structures.

4.3 Redesign for additive manufacturing

Experts and novices were asked Question 4 for the parts where TM was preferred over AM. This was presented to understand how they would redesign a product that was initially found suitable to be fabricated via TM (objective 3 in Sect. 1). Otherwise said, they were asked to suggest how to redesign the part for AM. By analyzing the eleven interview transcripts, the following suggestions/redesign ideas were

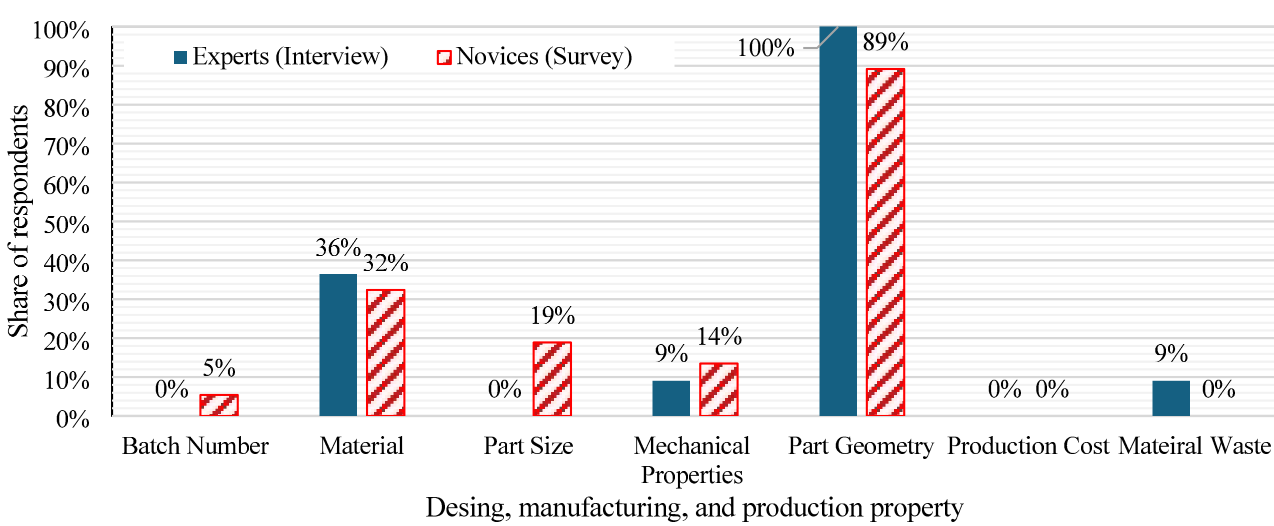


Fig. 6 Comparison of experts' (blue bars) and novices' (red-striped bars) manufacturing process selection considering Part 7

Table 8 Comparison of experts and novices to redesign for AM based on ISO standards

ISO standards to redesign for AM [71, 72]	Experts	Novices
Part Customization (TO or lattice)	Yes	Yes
Lightweighting	Yes	Yes
Use of internal channels or structures	Yes	Yes
Functional integration	Yes	No
Use of designed surface structures	Yes	Yes
Use of multi-material	No	No
Mechanical integrity	Yes	No

put forth by some of the experts to enhance a part's suitability for AM:

1. Some geometrical changes that would not require support structures during printing,
2. Applying TO to the part considering the mechanical integrity,
3. Reducing the scale (size) of the part,
4. Introducing lattice structures to the part while safeguarding mechanical constraints,
5. Decreasing the wall thickness of the part,
6. Redesigning the internal sections or channels.

By analyzing the survey results obtained from the answers to Question 4, the following points were the main novices' suggestions to redesign for AM:

a. Adjusting the geometry to avoid support structures,
b. Applying TO and weight reduction,
c. Changing the size and the material,
d. Redesigning the internal geometry,
e. Reducing the number of overhangs,

In summary, concerning objective 3, some experts and novices highlighted the aforementioned geometrical modifications to optimize designs for AM. Table 8 shows the differences between experts and novices considering the ISO standards for AM redesign. Both groups recognize the importance of geometrical modifications to optimize designs for AM, as shown in Table 8. However, the use of multi-material in a design was not mentioned by either group, and novices also failed to identify the function and mechanical integrity of parts. These findings underscore the need for further research and training to bridge the gap between experts and novices in AM design.

Consequently, in consideration of the geometrical modifications to make a part more suitable for AM, the provided answers were aligned with the literature in the cases of where AM was largely recognized as the preferred manufacturing technology [2].

5 Discussion

The primary focus of this article was to investigate the reasons behind selecting a manufacturing process by comparing expert and novice decision-making. The significant results achieved are as follows:

1. The majority of experts primarily considered seven manufacturing properties that emerged from text analysis of interview data, while a large number of novices overlooked production costs and material waste.
2. Novices were more likely to choose AM than experts.
3. Part geometry, material, and size were the three main properties considered when deciding whether a part is more suitable for fabrication via AM or TM.
4. The presence of specific features (e.g., lattice, thin walls, TO) was conducive to selecting AM for both groups.

Concerning the first point, this difference highlights the importance of experience and a comprehensive understanding of manufacturing processes. Experts' indications to consider material waste, cost, and other factors such as part size and geometry leads to efficient and cost-effective decisions. Conversely, novices may initially require additional guidance and training to develop a more holistic and detailed approach to process selection. These gaps can be bridged through education and mentorship, especially due to the limited emphasis placed on manufacturing process selection in educational contexts. In this regard, the few examples available in the literature of such experiences are non-generalizable and have a different focus, i.e., prioritizing local materials [73] and training AM specialists [74].

As for the second point, novices are naturally drawn to AM, as evidenced in the literature [68], due to its empowering user-friendly nature, design flexibility, and suitability for small-scale projects. The ease of iteration and quick feedback on designs further empower novices to explore new designs and innovate with AM. This is exacerbated by novices' preference for digital tools, necessary when AM is involved, to be used during design, as suggested by the case of the DfAM task reported in [75]. To highlight novices' difficulty working with traditional instruments in the domain of this research, it is worth noting that novices require software tools to improve the manufacturability of parts when they are administered DfAM tools [76] and to make DfAM-related evaluations [77]. Hence, the present paper adds a facet in DfAM research focused on novices and how they identify AM as a domain inherently linked to digital technologies.

Regarding the third point, TM's limitation in geometric complexity favors the selection of AM, while AM's limitation in part size favors TM.

As for the last point, the existence of specific features (e.g., lattice structures) resulted fundamental in preferring AM over TM, which aligns with common DfAM tools described in the literature, e.g [78]. Within DfAM, the identification of these features supports attempts to catalogue geometrical elements and attributes ascribable to AM as a required fabrication technology [79]. These features can be considered as cases in point of complex geometries that are difficult to obtain with TM technologies. Although TM, specifically investment casting, is able to generate relatively complex geometries, they usually require material removal, resulting in material waste.

The findings of this paper support that a fundamentally interdependent relationship exists between AM and part geometry, each enhancing and influencing the other. AM provides design freedom, enabling the creation of unique, customized, and complex geometries that TM cannot achieve. Despite the evidence that some design features lead to the choice of AM as a fabrication technology, a clear definition of design complexity for AM did not emerge. The lack of such a clear definition thus remains a gap in the DfAM literature, as evidenced in Sect. 2.2. Nevertheless, the results confirm the presence of some design characteristics that exclude AM as a manufacturing option or make it essential for fabrication. More investigation is needed because of the presence of a "gray zone", where none of these design characteristics are present and where most misalignment between experts and novices emerged. Markedly, as evidenced in Fig. 5, there are some cases where parts can be suitable for fabrication with either AM or TM technologies. The main reason behind this is the difficulty to draw a clear demarcation line between conditions that favor one manufacturing process over another.

The findings of this research could be used to enhance design education. Including activities on and case studies of manufacturing process selection could benefit the product development process. To bridge the gap between experts' and novices' decisions, manufacturing process selection can be introduced into design education. By introducing this into the curriculum, novices could be trained to consider a wider range of factors, enhancing design outcomes, and preparing novices for the complexity of the manufacturing world.

Another possible implication of the findings is the development of an ML algorithm based on the insights collected from experts and novices. To this end, a supervised deep learning algorithm could be developed, as suggested in the future work section of this study. The development of a ML-based system oriented to recognize the suitability of geometries for AM can well complement other efforts of integrating ML into DfAM, for example in the definition of designs process parameters [80]. An ML system able to both redesign by including typical DfAM characteristics, and the recognizing shapes already tailored for AM can well support the current trend of dual DfAM [81], i.e. mutually considering the opportunistic and restrictive nature of DfAM.

As mentioned, the paper demonstrates the existence of some features that make people potentially in charge of selecting a manufacturing process to opt for AM, whether experts or novices. Hence, the connection between specific design elements and AM is evident, not only in DfAM literature. A more widespread acknowledgment of this connection could enhance the acceptability of 3D-printed products, which is a further concern in DfAM research, e.g [82, 83]. Obviously, the acceptance of products and parts created with AM should at least involve those specific geometries that are increasingly recognized as DfAM elements. This is however hindered by one of the challenges acknowledged in DfAM literature, namely the limited awareness of AM benefits in some industries [84].

It is essential to recognize certain limitations that inevitably impact the scope and generalizability of findings. The identified limitations of this article are listed below:

- Convenience of using different methods for experts and novices, although possibly not affecting the results.
- Small samples of convenience, with novices being from a single institution.
- Limited sample of parts investigated, where the selection was partially arbitrary. The size of the sample is due to the need to limit the duration of interviews and surveys.

6 Conclusion and future work

This paper, which involved the participation of eleven manufacturing experts and thirty-seven engineering students, presents a comprehensive investigation into the reasons behind selecting a manufacturing process and the influence of part geometry in design and manufacturing. The research process included semi-structured interviews and surveys, with ten questions forming the backbone of both investigation methods. The following results are achieved by comparing the perspectives of these experts and novices:

- Seven manufacturing properties emerged as decision-making criteria in experts' manufacturing process selection based on the analysis of the interview data, suggesting that decisions made on the availability of part shapes only were taken through assuming some of the other six properties.

- Most novices failed to recognize production costs and material waste as criteria for selecting a manufacturing process, which shows a clear gap in design education.
- Compared to experts, novices leant towards selecting AM more frequently, although this difference is seldom statistically significant.
- Part geometry, material, and part size were identified as the most significant properties in selecting a manufacturing process, underscoring their importance in design and manufacturing.
- Both groups preferred AM when specific features (such as TO, lattice structures, or thin walls) were recognized in the parts, which is the main finding of the paper in relation to DfAM.

Although the two groups shared some similarities, the analysis revealed low agreement levels within each group when selecting a manufacturing process. The results of this research confirm that some design features make AM significant or exclude it from the production process. Further investigation is required as there is a “gray zone” where none of the influential design features is available and where the most misalignments occurred in this research. A potential demarcation line between geometries suitable for AM or TM clearly lies in this gray zone, which is nevertheless too large to guide manufacturing process selection accurately. Therefore, those parts for which major disagreement on most convenient manufacturing technology occurs should be given specific research attention.

Overall, the main contributions of this paper are:

- Highlighting seven manufacturing properties that are of fundamental importance for selecting an appropriate manufacturing process,
- Highlighting the role of manufacturing process selection in design education,
- Highlight the main differences between experts’ and novices’ decision-making,
- Proving the necessity to further investigate the “gray-zone” among manufacturing technologies, which is crucial in DfAM research.

Beyond further investigating the possibility to define what can be considered “designed for AM”, future work is devoted to developing a smart system that can support the decision-making for manufacturing process selection including but not limited to.

- Generating a process selection methodology that combines opinions of experts and novices to enhance decision-making in AM.
- Developing a deep learning algorithm using the seven manufacturing properties identified in this research.
- Developing a decision tree based on experts’ manufacturing process selection criteria.
- Developing a geometry evaluation guideline or framework to evaluate AM suitability considering expert insights.

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Declarations

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References

1. Dalpadulo, E., Pini, F., Leali, F.: Integrated CAD platform approach for design for additive manufacturing of high performance automotive components. Int. J. Interact. Des. Manuf. **14**, 899–909 (2020). https://doi.org/10.1007/S12008-020-00684-7
2. Pradel, P., Zhu, Z., Bibb, R., Moultrie, J.: A framework for mapping design for additive manufacturing knowledge for industrial and product design. J. Eng. Des. **29**, 291–326 (2018). https://doi.org/10.1080/09544828.2018.1483011
3. Plocher, J., Panesar, A.: Review on design and structural optimisation in additive manufacturing: Towards next-generation lightweight structures. Mater. Des. **183**, 108164 (2019). https://doi.org/10.1016/J.MATDES.2019.108164
4. Dong, G., Tang, Y., Zhao, Y.F.: A survey of modeling of lattice structures fabricated by additive manufacturing. J. Mech. Des. **139** (2017). https://doi.org/10.1115/1.4037305/367020
5. Ördek, B., Borgianni, Y., Coatanea, E.: Machine learning-supported manufacturing: A review and directions for future research. Prod. Manuf. Res. **12**, 2326526 (2024). https://doi.org/10.1080/21693277.2024.2326526
6. Achillas, C., Tzetzis, D., Raimondo, M.O.: Alternative production strategies based on the comparison of additive and traditional

manufacturing technologies. Int. J. Prod. Res. **55**, 3497–3509 (2017). https://doi.org/10.1080/00207543.2017.1282645

7. Cruz, M.F., Borille, A.V.: Decision methods application to compare conventional manufacturing process with metal additive manufacturing process in the aerospace industry. J. Brazilian Soc. Mech. Sci. Eng. **39**, 177–193 (2017). https://doi.org/10.1007/S40430-016-0532-8
8. Ghiasian, S.E., Jaiswal, P., Rai, R., Lewis, K.: From Conventional to Additive Manufacturing: Determining Component Fabrication Feasibility. In: Proceedings of the ASME Design Engineering Technical Conference. American Society of Mechanical Engineers Digital Collection (2018)
9. Ördek, B., Borgianni, Y.: HICA: A MATLAB-based hierarchical image clustering algorithm for classifying parts suitable for additive and traditional manufacturing technologies. SoftwareX. **27**, 101837 (2024). https://doi.org/10.1016/J.SOFTX.2024.101837
10. Ördek, B., Coatanea, E., Borgianni, Y.: An auto hierarchical clustering algorithm to distinguish geometries suitable for additive and traditional manufacturing technologies: Comparing humans and unsupervised learning. Results Eng. **25**, 104418 (2025). https://doi.org/10.1016/J.RINENG.2025.104418
11. Ördek, B., Borgianni, Y.: Differentiating additive and traditional manufacturing processes through unsupervised learning and image processing. In: Borgianni, Y., Matt, D.T., Molinaro, M., Orzes, G. (eds.) Towards a Smart, Resilient and Sustainable Industry, pp. 552–563. Springer Nature Switzerland, Cham (2023)
12. Ördek, B., Borgianni, Y.: Application of Unsupervised Learning and Image Processing into Classification of Designs to be Fabricated with Additive or Traditional Manufacturing. Proceedings of the Design Society. 3, 613–622 (2023). https://doi.org/10.1017/pds.2023.62
13. Pereira, T., Kennedy, J.V., Potgieter, J.: A comparison of traditional manufacturing vs additive manufacturing, the best method for the job. Procedia Manuf. **30**, 11–18 (2019). https://doi.org/10.1016/J.PROMFG.2019.02.003
14. Faludi, J., Bayley, C., Bhogal, S., Iribarne, M.: Comparing environmental impacts of additive manufacturing vs traditional machining via life-cycle assessment. Rapid Prototyp. J. **21**, 14–33 (2015). https://doi.org/10.1108/RPJ-07-2013-0067
15. Landi, D., Zefinetti, F.C., Spreafico, C., Regazzoni, D.: Comparative life cycle assessment of two different manufacturing technologies: Laser additive manufacturing and traditional technique. Procedia CIRP. **105**, 700–705 (2022). https://doi.org/10.1016/J.PROCIR.2022.02.117
16. Graziosi, S., Faludi, J., Stanković, T., Borgianni, Y., Meisel, N., Hallstedt, S.I., Rosen, D.W.: A vision for sustainable additive manufacturing. Nature Sustainability 1–8 (2024). (2024). https://doi.org/10.1038/s41893-024-01313-x
17. Terziyan, V., Gryshko, S., Golovianko, M.: Patented intelligence: Cloning human decision models for industry 4.0. J. Manuf. Syst. **48**, 204–217 (2018). https://doi.org/10.1016/J.JMSY.2018.04.019
18. Thompson, M.K., Moroni, G., Vaneker, T., Fadel, G., Campbell, R.I., Gibson, I., Bernard, A., Schulz, J., Graf, P., Ahuja, B., Martina, F.: Design for additive manufacturing: Trends, opportunities, considerations, and constraints. CIRP Ann. **65**, 737–760 (2016). https://doi.org/10.1016/J.CIRP.2016.05.004
19. Dordlofva, C., Törlind, P.: Evaluating design uncertainties in additive manufacturing using design artefacts: Examples from space industry. Des. Sci. **6** (2020). https://doi.org/10.1017/DSJ.2020.11
20. Huang, J., Chen, Q., Jiang, H., Zou, B., Li, L., Liu, J., Yu, H.: A survey of design methods for material extrusion polymer 3D printing. Virtual Phys. Prototyp. **15**, 148–162 (2020). https://doi.org/10.1080/17452759.2019.1708027
21. Liu, J., Ma, Y.: A survey of manufacturing oriented topology optimization methods. Adv. Eng. Softw. **100**, 161–175 (2016). https://doi.org/10.1016/J.ADVENGSOFT.2016.07.017
22. Vogiatzis, P., Chen, S., Zhou, C.: An open source framework for integrated additive manufacturing and Level-Set-Based topology optimization. J. Comput. Inf. Sci. Eng. **17** (2017). https://doi.org/10.1115/1.4037738/474348
23. Dunning, P.D.: Minimum length-scale constraints for parameterized implicit function based topology optimization. Struct. Multidisciplinary Optim. **58**, 155–169 (2018). https://doi.org/10.1007/S00158-017-1883-1
24. Liu, J.: Piecewise length scale control for topology optimization with an irregular design domain. Comput. Methods Appl. Mech. Eng. **351**, 744–765 (2019). https://doi.org/10.1016/J.CMA.2019.04.014
25. Liu, J., Zheng, Y., Ahmad, R., Tang, J., Ma, Y.: Minimum length scale constraints in multi-scale topology optimisation for additive manufacturing. Virtual Phys. Prototyp. **14**, 229–241 (2019). https://doi.org/10.1080/17452759.2019.1584944
26. Allaire, G., Bogosel, B.: Optimizing supports for additive manufacturing. Struct. Multidisciplinary Optim. **58**, 2493–2515 (2018). https://doi.org/10.1007/S00158-018-2125-X
27. Ceruti, A., Ferrari, R., Liverani, A.: Design for additive manufacturing using LSWM: A CAD tool for the modelling of lightweight and lattice structures. In: Campana, G., Howlett, R.J., Setchi, R., Cimatti, B. (eds.) Sustainable Design and Manufacturing 2017, pp. 756–765. Springer International Publishing, Cham (2017)
28. Yan, C., Hao, L., Hussein, A., Young, P., Raymont, D.: Advanced lightweight 316L stainless steel cellular lattice structures fabricated via selective laser melting. Mater. Des. **55**, 533–541 (2014). https://doi.org/10.1016/J.MATDES.2013.10.027
29. Jishi, H.Z., Umer, R., Cantwell, W.J.: The fabrication and mechanical properties of novel composite lattice structures. Mater. Des. **91**, 286–293 (2016). https://doi.org/10.1016/J.MATDES.2015.11.112
30. Vaissier, B., Pernot, J.P., Chougrani, L., Véron, P.: Parametric design of graded truss lattice structures for enhanced thermal dissipation. Comput. Aided Des. **115**, 1–12 (2019). https://doi.org/10.1016/J.CAD.2019.05.022
31. Zhang, J.Z., Sharpe, C., Seepersad, C.C.: Stress-Constrained design of functionally graded lattice structures with spline-Based dimensionality reduction. J. Mech. Des. **142** (2020). https://doi.org/10.1115/1.4046237/1074255
32. Ha, C.S., Lakes, R.S., Plesha, M.E.: Design, fabrication, and analysis of lattice exhibiting energy absorption via snap-through behavior. Mater. Des. **141**, 426–437 (2018). https://doi.org/10.1016/J.MATDES.2017.12.050
33. Daynes, S., Feih, S.: Bio-inspired lattice structure optimisation with strain trajectory aligned trusses. Mater. Des. **213**, 110320 (2022). https://doi.org/10.1016/J.MATDES.2021.110320
34. Almalki, A., Downing, D., Noronha, J., Dash, J., Lozanovski, B., Tino, R., Alghamdi, A., Khorasani, M., Qian, M., Brandt, M., Leary, M.: The effect of geometric design and materials on section properties of additively manufactured lattice elements. Int. J. Adv. Manuf. Technol. **126**, 3555–3577 (2023). https://doi.org/10.1007/S00170-023-11251-1
35. Shea, K., Aish, R., Gourtovaia, M.: Towards integrated performance-driven generative design tools. Autom. Constr. **14**, 253–264 (2005). https://doi.org/10.1016/J.AUTCON.2004.07.002
36. Li, X., Xie, C., Sha, Z.: Design representation for performance evaluation of 3D shapes in structure-aware generative design. Des. Sci. **9**, e27 (2023). https://doi.org/10.1017/DSJ.2023.25
37. McKnight, M.: Generative design: What it is? How is it being used? Why it's a game changer. KnE Eng. **2**, 176 (2017). https://doi.org/10.18502/KEG.V2I2.612

38. Valjak, F., Lindwall, A., REVIEW OF DESIGN HEURISTICS AND DESIGN PRINCIPLES IN DESIGN FOR ADDITIVE MANUFACTURING:. In: Proceedings of the Design Society. pp. 2571–2580. Cambridge University Press (2021)
39. Blösch-Paidosh, A., Shea, K.: Design Heuristics for Additive Manufacturing - Research Collection. In: Maier, A., Skec, S., Kim, H., Kokkolaras, M., Oehmen, J., Fadel, G., and Salustri, F. (eds.) Proceedings of the 21st International Conference on Engineering Design: Design for X, Design to X. pp. 91–100. The Design Society, Vancouver, Canada (2017)
40. Blösch-Paidosh, A., Shea, K.: Industrial evaluation of design heuristics for additive manufacturing. Des. Sci. **8** (2022). https://doi.org/10.1017/DSJ.2022.8 e13
41. Lindwall, A., Törlind, P., Evaluating Design Heuristics for Additive Manufacturing as an Explorative Workshop Method:. In: Marjanović, D., Štorga, M., Škec, S., Bojčetić, N., and Pavković, N. (eds.) DS 92: Proceedings of the DESIGN 2018 15th International Design Conference. pp. 1221–1232 (2018)
42. Blosch-Paidosh, A., Shea, K.: Enhancing creative redesign through multimodal design heuristics for additive manufacturing. J. Mech. Des. **143**, 102003–102004 (2021). https://doi.org/10.1115/1.4050656/1105207
43. Blösch-Paidosh, A., Shea, K.: Design heuristics for additive manufacturing validated through a user study. J. Mech. Des. **141** (2019). https://doi.org/10.1115/1.4041051/366976
44. Kiernan, L., Ledwith, A., Lynch, R.: Comparing the dialogue of experts and novices in interdisciplinary teams to inform design education. Int. J. Technol. Des. Educ. **30**, 187–206 (2020). https://doi.org/10.1007/S10798-019-09495-8
45. Deken, F., Kleinsmann, M., Aurisicchio, M., Lauche, K., Bracewell, R.: Tapping into past design experiences: Knowledge sharing and creation during novice-expert design consultations. Res. Eng. Des. **23**, 203–218 (2012). https://doi.org/10.1007/S00163-011-0123-8
46. Cross, N.: Expertise in design: An overview. Des. Stud. **25**, 427–441 (2004). https://doi.org/10.1016/J.DESTUD.2004.06.002
47. Fillingim, K.B., Nwaeri, R.O., Paredis, C.J.J., Rosen, D., Fu, K.: Examining the effect of design for additive manufacturing rule presentation on part redesign quality. J. Eng. Des. 427–460 (2020). https://doi.org/10.1080/09544828.2020.1789569
48. Hwang, D., Perez, B., Anderson, K., Jensen, D., Camburn, D., Wood, B.: Design principles for additive manufacturing: Leveraging crowdsourced design repositories. J. Mech. Des. **143** (2021). https://doi.org/10.1115/1.4050873/1107063
49. Prabhu, R., Simpson, T.W., Miller, S.R., Meisel, N.A.: Mastering manufacturing: Exploring the influence of engineering designers' prior experience when using design for additive manufacturing. J. Eng. Des. **33**, 366–387 (2022). https://doi.org/10.1080/09544828.2022.2075222
50. Schniederjans, D.G., Yalcin, M.G.: Perception of 3D-printing: Analysis of manufacturing use and adoption. Rapid Prototyp. J. **24**, 510–520 (2018). https://doi.org/10.1108/RPJ-04-2017-0056
51. Velloso, L.M.R., Barros, G.: Recurrent techniques used in UX design: A report from user survey and interviews with professional designers. J. Des. Res. **21**, 47–61 (2023). https://doi.org/10.1504/JDR.2023.133264
52. Pack, A.T., Phipps, E.R., Mattson, C.A., Dahlin, E.C.: Social impact in product design, an exploration of current industry practices. J. Mech. Des. **142** (2020). https://doi.org/10.1115/1.4045448/1068299
53. Ördek, B., Borgianni, Y.: Reasons behind selecting a manufacturing process: A Semi-structured interview study. In: Di Stefano, P., Gherardini, F., Nigrelli, V., Rizzi, C., Sequenzia, G., Tumino, D. (eds.) Design Tools and Methods in Industrial Engineering IV. ADM 2024. Lecture Notes in Mechanical Engineering, pp. 12–19. Springer, Cham (2025)
54. Lee, S.H., Yang, M., De Weck, O.L., Lee, C., Coughlin J.F., Klopfer, E., Ochsendorf, J.: SERVICE DESIGN IN ACTION: TRANSFORMATION, CONSIDERATION, AND SYSTEM THINKING. Proc. Des. Soc. **3**, 3145–3154 (2023). https://doi.org/10.1017/PDS.2023.315
55. Lee, J.W., Daly, S.R., Vadakumcherry, V., Rodriguez, G.: Idea generation, development and selection: A study of mechanical engineering students' natural approaches and the impact of hybrid learning blocks. Des. Sci. **9**, e29 (2023). https://doi.org/10.1017/DSJ.2023.26
56. Li, S., Wang, R.: The role of machine learning in the development of intelligent manufacturing under the background of industry 4.0. Soft comput. 1–9 (2023). https://doi.org/10.1007/S00500-023-08105-Z
57. Agyemang, M., Turner, C.: J The presence of culture in student designer perceptions when making design requirements: A pilot study. Proc. ASME Des. Eng. Tech. Conf. **8** https://doi.org/10.1115/DETC2020-22558 (2020)
58. Karana, E., Hekkert, P., Kandachar, P.: Material considerations in product design: A survey on crucial material aspects used by product designers. Mater. Des. **29**, 1081–1089 (2008). https://doi.org/10.1016/J.MATDES.2007.06.002
59. Schrepp, M., Hinderks, A., Thomaschewski, J.: Applying the user experience questionnaire (UEQ) in different evaluation scenarios. In: Lecture Notes in Computer Science (including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), pp. 383–392. Springer, Cham (2014)
60. Carfagni, M., Fiorineschi, L., Furferi, R., Governi, L., Rotini, F.: Usefulness of prototypes in conceptual design: Students' view. Int. J. Interact. Des. Manuf. **14**, 1305–1319 (2020). https://doi.org/10.1007/S12008-020-00697-2
61. Dandan, T.H., Sweis, G., Sukkari, L.S., Sweis, R.J.: Factors affecting the accuracy of cost estimate during various design stages. J. Eng. Des. Technol. **18**, 787–819 (2020). https://doi.org/10.1108/JEDT-08-2019-0202
62. Bao, Q., Shaukat, M.M., Yang, M.C.: Eliciting user preference for quantitative vs. emotional information display in eco-feedback designs. Res. Eng. Des. **33**, 53–68 (2022). https://doi.org/10.1007/S00163-021-00363-Y
63. Korolev, P., Sosnin, A., Ivanov, I.: Development of the Dependability and Quality Assessment Method for the Design of Wireless Devices. In: International Seminar on Electron Devices Design and Production, SED 2021 - Proceedings. Institute of Electrical and Electronics Engineers Inc. (2021)
64. Siddharth, L., Blessing, L., Luo, J.: Natural Language processing in-and-for design research. Des. Sci. **8**, e21 (2022). https://doi.org/10.1017/DSJ.2022.16
65. Demšar, J., Curk, T., Erjavec, A., Gorup, Č., Hočevar, T., Milutinovič, M., Možina, M., Polajnar, M., Toplak, M., Starič, A., Štajdohar, M., Umek, L., Žagar, L., Žbontar, J., Žitnik, M., Zupan, B.: Orange: Data mining toolbox in python. J. Mach. Learn. Res. **14**, 2349–2353 (2013). https://doi.org/10.5555/2567709.2567736
66. Ishak, A., Siregar, K., Asfriyati, Ginting, R., Afif, M.: Orange software usage in data mining classification method on the dataset lenses. IOP Conf. Ser. Mater. Sci. Eng. **1003**, 012113 (2020). https://doi.org/10.1088/1757-899X/1003/1/012113
67. Marzi, G., Balzano, M., Marchiori, D.: K-Alpha Calculator–Krippendorff's alpha calculator: A user-friendly tool for computing krippendorff's alpha inter-rater reliability coefficient. MethodsX. **12**, 102545 (2024). https://doi.org/10.1016/j.mex.2023.102545
68. Booth, J.W., Alperovich, J., Chawla, P., Ma, J., Reid, T.N., Ramani, K.: The design for additive manufacturing worksheet. J. Mech. Des. **139** (2017). https://doi.org/10.1115/1.4037251/366998

69. Gibson, I., Rosen, D., Stucker, B.: Design for additive manufacturing. In: Additive Manufacturing Technologies, pp. 399–435. Springer (2015)
70. Rosen, D.W.: Research supporting principles for design for additive manufacturing. Virtual Phys. Prototyp. **9**, 225–232 (2014). https://doi.org/10.1080/17452759.2014.951530
71. ISO/ASTM 52911-1:2018: Additive manufacturing — Design — Requirements, guidelines and recommendations: (2018)
72. Vaneker, T., Bernard, A., Moroni, G., Gibson, I., Zhang, Y.: Design for additive manufacturing: Framework and methodology. CIRP Ann. **69**, 578–599 (2020). https://doi.org/10.1016/J.CIRP.2020.05.006
73. Pikkarainen, A., Piili, H., Salminen, A., Journal, E., INTRODUCING NOVEL LEARNING OUTCOMES AND PROCESS SELECTION MODEL FOR ADDITIVE MANUFACTURING EDUCATION IN ENGINEERING: Eur. J. Educ. Stud. **8**, 65 (2020). https://doi.org/10.46827/EJES.V8I1.3511
74. Souza, A., Almendra, R., Krucken, L.: Materials & manufacturing methods selection in product design: Experiences in undergraduate programs. Des. J. **20**, S1185–S1196 (2017). https://doi.org/10.1080/14606925.2017.1353060
75. Prabhu, R., Cass, M.: Sketch, CAD, or simulate the build? Exploring novice designers' design representation use in design for additive manufacturing. Int. J. Des. Creativity Innov. **12**, 215–237 (2024). https://doi.org/10.1080/21650349.2024.2391305
76. Budinoff, H.D., McMains, S., Shonkwiler, S.: Exploring the impact of design tool usage on design for additive manufacturing processes and outcomes. Des. Sci. **10**, e1 (2024). https://doi.org/10.1017/DSJ.2023.34
77. Meisel, N.A., Mathur, J., Cayley, A.: Creation and assessment of a novel design evaluation tool for additive manufacturing. J. Mech. Des. **146** (2024). https://doi.org/10.1115/1.4063566/1167725
78. Nieto, D.M., Sánchez, D.M.: Design for Additive Manufacturing: Tool Review and a Case Study. Applied Sciences 2021, Vol. 11, Page 1571. 11, 1571 (2021). https://doi.org/10.3390/APP11041571
79. Adam, G.A.O., Zimmer, D.: On design for additive manufacturing: Evaluating geometrical limitations. Rapid Prototyp. J. **21**, 662–670 (2015). https://doi.org/10.1108/RPJ-06-2013-0060
80. Trovato, M., Belluomo, L., Bici, M., Prist, M., Campana, F., Cicconi, P.: Machine learning in design for additive manufacturing: A state-of-the-art discussion for a support tool in product design lifecycle. Int. J. Adv. Manuf. Technol. 2025. **137**(5), 137, 2157–2180 (2025). https://doi.org/10.1007/S00170-025-15273-9
81. Dash, S., Nordin, A., Johansson, G.: Dual design for additive manufacturing in engineering design: A systematic literature review. Rapid Prototyp. J. **31**, 40–61 (2025). https://doi.org/10.1108/RPJ-06-2024-0245
82. Felton, H., Yon, J., Hicks, B.: Improving the feel of 3D printed prototypes for new product development: A feasibility study of emulating mass properties by optimising infill structures and materials. Des. Sci. **9**, e19 (2023). https://doi.org/10.1017/DSJ.2023.18
83. Borgianni, Y., Maccioni, L., Basso, D.: Exploratory study on the perception of additively manufactured end-use products with specific questionnaires and eye-tracking. Int. J. Interact. Des. Manuf. **13**, 743–759 (2019). https://doi.org/10.1007/S12008-019-00563-W
84. Murugan, R.S., Vinodh, S.: Holistic review on design for additive manufacturing. Progress in Additive Manufacturing 10, 4497–4532 (2024). (2024). 10:8 https://doi.org/10.1007/S40964-024-00887-4