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ORIGINAL ARTICLE

Selecting the most suitable 3D printing technology for custom manufacturing using fuzzy decision-making methodology

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Abstract

The rapid advancements in 3D printing technologies have significantly reshaped the manufacturing landscape, enabling highly customized and efficient production processes. However, selecting the most appropriate 3D printing technology for custom manufacturing is a complex decision that requires careful consideration of multiple, often conflicting criteria. Addressing this challenge, this study introduces a novel Fermatean fuzzy multi-criteria decision-making (MCDM) framework to facilitate informed technology selection. The proposed methodology combines the Best–Worst Method for weighting criteria with the Fermatean Fuzzy Weighted Aggregated Sum Product Assessment (FF-WASPAS) method for ranking alternatives, marking the first application of this hybrid approach in the literature. To demonstrate the framework, six leading 3D printing technologies were evaluated across nine critical criteria: Cost, Precision and Surface Quality, Finishing Requirement, Production Speed, Material Compatibility, Functional Durability, Ability to Manufacture Complex Geometry, Environmental Impact, and Technological Maturity. The analysis identified Stereolithography (SLA) as the best alternative for custom manufacturing, with the most critical criteria being Precision and Surface Quality, Functional Durability, and Ability to Manufacture Complex Geometry. This study offers a systematic and robust decision-making framework, providing valuable guidance for manufacturing authorities in selecting the most suitable 3D printing technology for customized applications.

Keywords 3D printing technology · Custom manufacturing · Multi-criteria decision-making · Fermatean fuzzy sets

1 Introduction

Custom manufacturing, also known as bespoke or tailored manufacturing, is the creation of products that are specifically designed and produced to meet unique customer Technique for Order Preference by Similarity to Ideal Solutions [1]. In contrast to mass production, custom manufacturing emphasizes flexibility and adaptability. It allows manufacturers to respond to diverse customer needs with precision. In today's fast-evolving industries, the growing demand for personalized products, technological advancements, and the rise of Industry 4.0 make custom manufacturing increasingly important. This approach not only increases customer satisfaction, but also provides a competitive advantage. It enables companies to innovate, reduce waste, and effectively serve niche markets. Companies use significant financial resources to invest in new production models along with advanced production technologies in order to respond to rapidly changing production processes and customer demands, to recognize and apply new production technologies [2]. And, in the production and design stages of products, in addition to the perception of low cost and high quality, the use of technological tools also comes to the fore [3]. 3 dimensions (3D) printing technologies, which offer unparalleled precision, scalability, and efficiency in manufacturing processes, have emerged as transformative tools as a key enabler of customization.

The concept of 3D printing denotes to widespread technological advances and processes that allow the production of goods and components using a wide variety of materials [4].

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3D printing, also known as additive manufacturing, is a popular technology that allows instant creation of 3D objects layer by layer fashion [5]. 3D printing technologies have revolutionized custom manufacturing. They enable the creation of highly complex and personalized products with exceptional efficiency and accuracy. Especially when compared to subtractive manufacturing, it has advantages such as relatively shorter product production time, material savings, the ability to develop complex geometries and shapes, and durability [6]. 3D printing builds products layer by layer, minimizing waste and reducing production time, unlike traditional manufacturing methods that often require extensive tooling and material waste. This capability makes it an ideal choice for custom manufacturing, where flexibility and precision are paramount. In industries such as healthcare, aerospace, automotive and consumer goods, the role of 3D printing extends beyond prototyping to the production of end-use parts. It allows manufacturers to create complex geometries that were previously impossible or cost prohibitive using traditional methods.

By enabling rapid design iterations and on-demand production, 3D printing technologies are improving the personalization process, shortening lead times, streamlining supply chains, and fostering innovation, cementing their position as a cornerstone of modern manufacturing. This technology is frequently used in markets with special and high-value production chains because it provides fast production advantages and does not require a mold [7]. Production becomes more customized, as each part is personalized to meet the specific needs of each customer [8]. Additionally, 3D printing technologies offer more affordable solutions than traditional customization technologies for manufacturers to offer better flexibility and product options to meet their demands [9]. Thanks to these features, this technology has the potential to reduce or completely eliminate the use of traditional tools, reduce failures, enable fully customized designs with software modeling, and significantly reduce the cost of production [10].

In the industrial sector, 3D printing is used to design and manufacture prototypes, components or finished products in almost all manufacturing sectors. This defines a growing market where 3D printing makes a significant contribution to industrial applications [11]. Especially, Custom products require more flexible and smarter technologies that are often not compatible with the production flow. And, to efficiently produce customized product features in custom manufacturing, the workflow for consecutive jobs can be very different and part routing patterns can be complex and variable [8].

This growing dependence on 3D printing highlights the critical need to select the most appropriate technology for specific custom manufacturing applications. Each 3D printing technology offers unique capabilities and limitations, making the selection process a multifaceted decision. Identifying the most appropriate 3D printing technology is essential to optimizing production efficiency, ensuring product quality, and maintaining a competitive edge in a rapidly evolving marketplace. As sustainability becomes increasingly important, the choice of technologies that reduce waste and energy consumption is a support to environmentally responsible manufacturing practices. All in all, choosing the right 3D printing technology is a strategic decision that impacts both the immediate results and the long-term goals of the industry.

The main objective of this study is to identify the most suitable 3D printing technology for custom manufacturing by employing an advanced Fermatean fuzzy multi-criteria decision-making approach. This involves integrating the Best–Worst Method (BWM) for determining the relative importance of criteria with the Fermatean Fuzzy Weighted Aggregated Sum Product Assessment (FF-WASPAS) method for evaluating and ranking alternatives. By focusing on six leading 3D printing technologies and analyzing them against multiple criteria, the study aims to provide a robust and comprehensive framework for decision-makers in custom manufacturing. Ultimately, this research contributes to the body of knowledge by introducing a novel methodology for tackling complex selection problems while offering actionable insights for practitioners in the field.

Multi Criteria Decision Making (MCDM) approaches provide practical and effective solutions from a broad perspective by considering many criteria in decision-making processes. In the limited number of studies related to 3D printing, traditional methods such as Technique for Order Preference by Similarity to Ideal Solutions (TOPSIS), (Preference Ranking Organisation Method For Enrichment Evaluation) PROMETHEE, (Analytical Hierarchy Process) AHP or (The Decision Making Trial and Evaluation Laboratory) DEMATEL have been used for material, technology or strategy selection in different application areas [3, 12–14]. This study purposes to address the challenge of selecting the most suitable 3D printing technology for custom manufacturing industry by using advanced MCDM methods. For this aim, in order to selection of 3D printing technologies to be used in custom manufacturing, nine critical criteria *(Cost, Precision and Surface Quality, Finishing Requirement, Production Speed, Material Compatibility, Functional Durability, Ability to Manufacture Complex Geometry, Environmental Impact, Technological Maturity)* are determined by using literature review and expert opinions. Then, to select the most suitable one among alternative 3D printing technologies according to these criteria, BWM and FF-WASPAS methods are integrated. In other words, in the first step of the proposed methodology, the criteria are weighted with the BWM and the FF-WASPAS method is applied using these criteria weights and finally the alternative technologies are

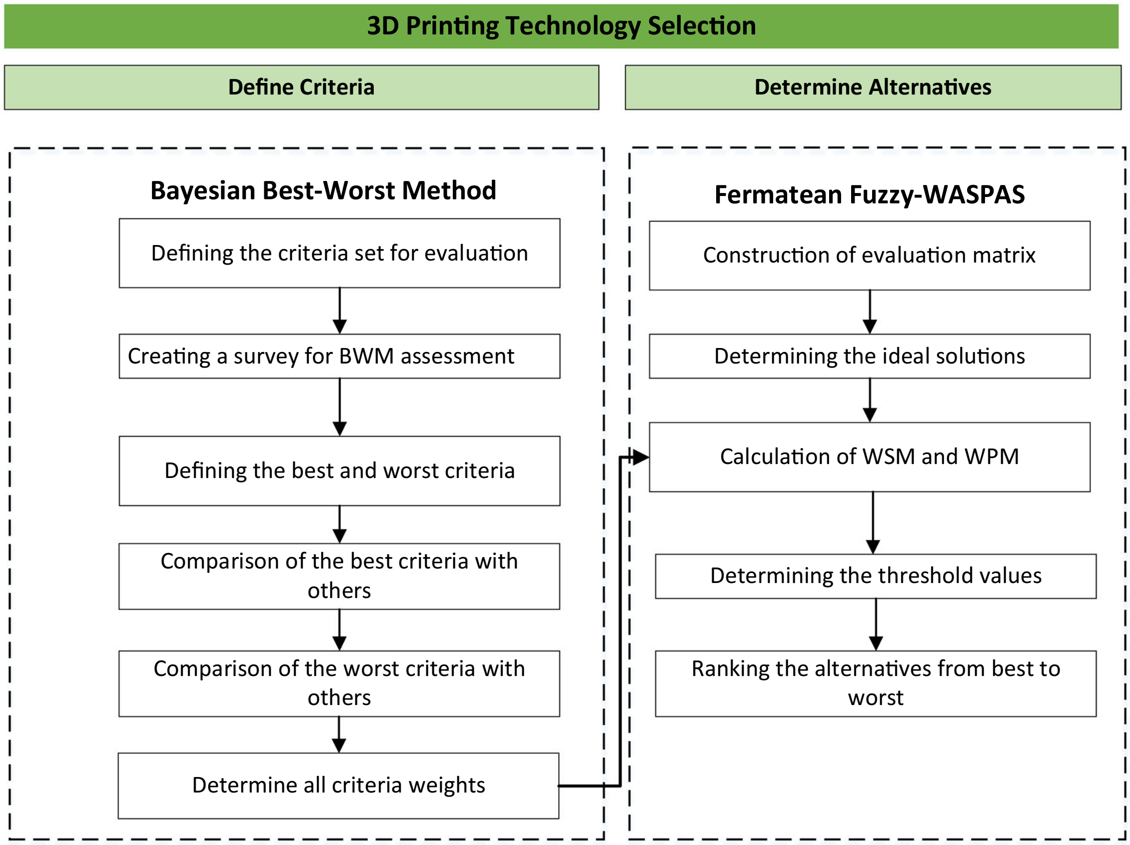

Fig. 1 The proposed hybrid methodology

ranked according to the scores. Thus, this study offers strategic advantages to custom manufacturing company managers to ensure customer satisfaction in a competitive environment and rapidly changing technological conditions.

The main contributions of this paper are:

- For 3D printing, studies have generally been conducted in the fields of material, strategy selection, and chemistry and dental sectors. Also, in the limited number of studies conducted using MCDM approaches, the criteria were selected by focusing on general features. This study offers comprehensive criteria with the requirements of 3D printing technology.
- The most suitable 3D printing technology is determined by employing a novel hybrid MCDM approach.
- Different from the literature, BWM and FF-WASPAS methods within the fuzzy environment are integrated, providing a pioneering framework for decision-making in custom manufacturing. The BWM method is applied for the first time in order to weigh the criteria, and the FF-WASPAS method is used to obtain the scores of alternative 3D printing technologies by using the obtained weights.
- With this study, the new methodology is included in the decision-making literature, filling a gap by providing a robust tool for handling uncertainty in multi-criteria valuations to confirm the sustainability and efficiency of the custom manufacturing process.

The integration of BWM and FF-WASPAS offers several practical advantages over other existing MCDM methodologies. Unlike conventional methods, such as AHP or TOPSIS, which often require extensive pairwise comparisons or rely on linear normalization techniques, the proposed hybrid approach combines the strengths of both BWM and FF-WASPAS. BWM minimizes inconsistency in criteria weighting by reducing the number of comparisons required and focusing on the most and least important criteria, enhancing decision accuracy and efficiency. FF-WASPAS, on the other hand, provides a robust ranking mechanism by incorporating both the weighted sum and weighted product models, allowing for a comprehensive evaluation of alternatives. Additionally, the Fermatean fuzzy environment enables better handling of uncertainty and hesitation in expert opinions compared to traditional crisp or intuitionistic fuzzy approaches. This hybrid approach is particularly effective in complex decision-making scenarios, such as selecting 3D printing technologies, where conflicting criteria must be evaluated simultaneously. By combining these methods, the proposed framework delivers more reliable and practical results, making it a valuable tool for decision-makers in real-world applications.

The paper is organized as follows. In Sect. 2, literature review is presented. Section 3 summaries the framework structure of the proposed methodology. Section 4 suggest the case study and discussion of the results are stated in Sect. 5. In the last section conclusion and directions for future work is given.

2 Literature review

Studies in the field of selection regarding 3D printing are limited in the literature. Lai and Chang [2] proposed a two-stage procedure for 3D technology introduction. In the first stage of this procedure, the fuzzy Delphi method was used to determine the criteria. As a result, criteria based on environment, resource, strategy, technique and operational performance were determined. Then, the criteria were weighted using the AHP method. Raja and Rajan [12] selected nine machines based on the views of 172 experts, all of whom were machine users, to choose the best 3D printing for prototyping in the medical and construction sectors. These are factors such as printing speed, environment, cost and security. Algunaid and Liu [13] considered the selection process of 3D printing service. Accordingly, they defined criteria based on performance and sustainability. They used techniques such as AHP, DEMATEL, TOPSIS to obtain criteria weights and evaluate ten systems. The most suitable 3D printing technology selection study for prosthesis production was presented by Alakaş et al., [14]. In this study, the criterion weights were determined by AHP, which is one of the basic MCDM methods, while TOPSIS and PROMETHEE methods were applied to rank the alternatives. 10 alternatives, were evaluated according to the resolutions, resistance, sensibility, smoothness and cost criteria.

Studies in the literature have presented applications for 3D printing machine/technology selection in both a limited number and a narrow criteria perspective. 3D printing selection is important especially for companies that do personal production such as custom manufacturing. Therefore, a broad criteria perspective should be considered in order to facilitate the decision-making processes of companies. In addition, fuzzy-based methods should be used to make the decision-making process more efficient and to reduce the complexity of the problem. Table 1 summarizes studies on 3D printing selection.

Several state-of-the-art investigations have explored the effectiveness, advantages, and disadvantages of BWM and FF-WASPAS. For instance, studies have shown that BWM requires fewer pairwise comparisons than AHP, which significantly reduces the time and effort required for data collection and analysis [16]. However, BWM's reliance on a fixed scale for pairwise comparisons can sometimes lead to inconsistencies, especially when dealing with highly subjective criteria [17]. In contrast, FF-WASPAS has been praised for its ability to handle linguistic variables and fuzzy data, making it particularly suitable for problems where human judgment plays a significant role [18]. Nevertheless, the method's computational complexity and the need for expert knowledge to define fuzzy sets can be seen as limitations [19]. Given these considerations, the selection of BWM and FF-WASPAS for this study is justified by their complementary strengths in addressing the specific challenges of our research problem.

Table 1 Application for 3D printing selection

References	Aims	Application area	Method
[12]	3D printing machine selection	Fusion deposition modeling machine production	Fuzzy TOPSIS
[13]	Machine and material selection	Additive manufacturing	DEMATEL, AHP, TOPSIS
[14]	Technology selection	Mold production	TOPSIS, PROMETHEE
[15]	Material selection	Image recognition technology	Deep learning models
[2]	Technology assessment	Mold production	Fuzzy Delphi, fuzzy hierarchical analysis
This study	Technology selection	Custom manufacturing	BWM, FF-WASPAS

3 The proposed methodology

This study proposes a novel fuzzy logic-integrated MCDM approach to identify the most suitable 3D printing technology for custom manufacturing. The methodology distinguishes itself through the unique integration of the BWM and FF-WASPAS, specifically tailored to address the challenges of 3D printing technology selection. Unlike conventional approaches, this hybrid model leverages BWM's structured weighting mechanism to enhance consistency in criteria prioritization, while FF-WASPAS is employed to rank alternatives, ensuring a comprehensive and flexible evaluation process. By combining BWM and FF-WASPAS, the proposed approach offers a robust framework for decision-making under uncertainty. This integration represents a key contribution of the study, as it addresses the limitations of

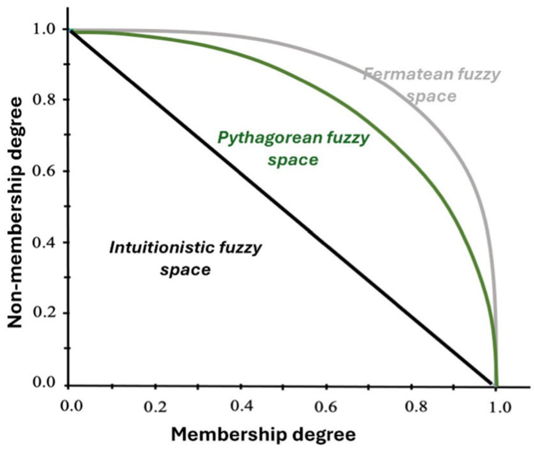

Fig. 2 Comparison of spaces for IFNs, PFNs, and FFNs

standalone methods and provides a more holistic solution to complex selection problems.

To clarify, the methodology is not merely a repetition of existing methods but an innovative adaptation designed to meet the specific challenges of custom manufacturing. For instance, modifications are introduced to the FF-WASPAS method to better handle the imprecision and subjectivity inherent in expert evaluations of 3D printing technologies. The procedural steps of this hybrid approach—including the structured expert judgment process, weight determination, and alternative ranking—are outlined in detail in Fig. 1, ensuring a systematic and transparent decision-making process. By emphasizing the novelty and practical applicability of the proposed methodology, this study aims to advance the field of MCDM and contribute to the growing body of research on 3D printing technology selection. Fig. 2

3.1 Best worst method

The BWM, developed by Rezaei [20], is a decision-making approach designed to simplify how criteria are weighted. It was introduced as an improvement over the Analytic Hierarchy Process (AHP), which requires multiple pairwise comparisons, often leading to inconsistencies. In AHP, when there are n criteria, decision-makers must make at least *n(n-1)/2* comparisons, which can be time-consuming and complex [16, 20]. BWM simplifies this process by focusing only on two reference points: the best (most important) and the worst (least important) criteria [21]. Experts compare each criterion only against these two, reducing the number of required comparisons. Since the worst criterion has already been compared to the best, fewer comparisons are needed, making the process more efficient. While AHP provides a broader set of comparisons, BWM achieves similar insights with a more structured and straightforward approach. The BWM's systematic process consists of the following steps:

Step 1.1. Define the decision criteria. Experts identify a set of n evaluation criteria relevant to the decision problem.

Step 1.2. Identify the best and worst criteria. Based on their expertise, each decision-maker selects the criterion they consider most important (C_B, the best) and least important (C_W, the worst) from the criteria set.

Step 1.3. Rate the best criterion against all others. Using a nine point-likert scale, decision-makers assess the best criterion's relative importance over each remaining criterion, producing a "best-to-others" vector$A_B = (a_{B1}, ..., a_{Bj}, \ldots, a_{Bn})$, where a_{BJ} represents the strength of preference for the best criterion over criterion C_j (excluding itself, where$a_{BB} = 1$).

Step 1.4. Rate all criteria against the worst. Decision-makers then assess each criterion's importance over the worst criterion, generating an "others-to-worst" vector$A_w = (a_{1W}, ..., a_{jW}, \ldots, a_{nW})^T$, where a_{jW} represents the preference of criterion C_j over the worst.

Step 1.5. Calculate optimal weights. The criteria weights are determined proportionally to the preference scores. The conditions $w_B/w_j^1 = a_{Bj}$ and $w_j^1/w_W = a_{jW}$ are applied, with weights $w_1^1, w_2^1, \ldots, w_n^1$ optimized to minimize deviations from these ratios. This is formulated as a minimization problem:

$$\min \xi \tag{1}$$

s.t.

$$\left| \frac{w_B}{w_j^1} - a_{Bj} \right| \le \xi, \forall_j \tag{2}$$

$$\left| \frac{w_j^1}{w_W} - a_{jW} \right| \le \xi, \forall_j \tag{3}$$

$$\sum_j w_j^1 = 1 \tag{4}$$

$$w_j \ge 0, \forall_j \tag{5}$$

3.2 Fermatean fuzzy WASPAS

Senapati and Yager introduced the concept of Fermatean Fuzzy sets (FFSs) as an advancement on Intuitionistic Fuzzy sets (IFSs) and Pythagorean Fuzzy sets (PFSs), aiming to more accurately represent uncertain and imprecise information [22]-[23]. FFSs are designed to capture a deeper level of ambiguity, employing a third parameter to quantify indeterminacy, or uncertainty regarding membership [24]-[25]. Like IFSs and PFSs, FFSs use a membership and a non-membership degree; however, FF sets add the constraint that the sum of the cubes of these three degrees (membership, non-membership, and indeterminacy) equals 1, allowing a more flexible representation of uncertain knowledge. It is important to note that the key distinction between FFSs, IFSs, and PFSs lies in their respective constraints. Figure 1a illustrates a comparison of the spaces of Fermatean Fuzzy Numbers (FFNs), Pythagorean Fuzzy Numbers (PFNs), and IFNs, demonstrating that the space of an FFN is broader than that of PFNs and Intuitionistic Fuzzy Numbers (IFNs). Consequently, FFSs are not only capable of representing uncertain information that PFSs and IFSs can handle but also excel at modeling more ambiguous and uncertain information that the latter two cannot effectively capture [26, 27]. (Fig. 2)

Mathematically, FFNs are defined within a set X as [22, 28]:

$$\widetilde{\mathrm{F}} \cong \left\{x, \mu_{\widetilde{F}}(x), v_{\widetilde{F}}(x); x \in X\right\} \tag{6}$$

$\mu_{\widetilde{F}}(x) : X \mapsto [0,1]$ represents the membership function and $v_{\widetilde{F}}(x) : X \mapsto [0,1]$ non-membership function. For these functions, the following constraint applies:

$$0 \leq \mu_{\widetilde{F}}(x)^3 + v_{\widetilde{F}}(x)^3 \leq 1 \tag{7}$$

The indeterminacy is calculated as.

$$\pi_{\widetilde{F}}(x) = \sqrt[3]{1 - (\mu_{\widetilde{F}}(x))^3 + (v_{\widetilde{F}}(x)^3)} \tag{8}$$

Basic mathematical operations on FFNs are defined as follows. where $\widetilde{\alpha} = (\mu_{\widetilde{\alpha}}, v_{\widetilde{\alpha}})$ and $\widetilde{\beta} = (\mu_{\widetilde{\beta}}, v_{\widetilde{\beta}})$ represent two FFNs and λ is a positive scalar [25–27]:

Scalar multiplication:

$$\lambda\widetilde{\alpha} = \left(\sqrt[3]{1 - \left(1 - \mu_{\widetilde{\alpha}}^3\right)^{\lambda}}, v_{\widetilde{\alpha}}^{\lambda}\right) \tag{9}$$

Power operation:

$$\widetilde{\alpha}^{\lambda} = \left(\mu_{\widetilde{\alpha}}^{\lambda}, \sqrt[3]{1 - \left(1 - v_{\widetilde{\alpha}}^3\right)^{\lambda}}\right) \tag{10}$$

Addition of FFNs:

$$\widetilde{\alpha} \oplus \widetilde{\beta} = \left(\sqrt[3]{\mu_{\widetilde{\alpha}}^3 + \mu_{\widetilde{\beta}}^3 - \mu_{\widetilde{\alpha}}^3\mu_{\widetilde{\beta}}^3}, v_{\widetilde{\alpha}}v_{\widetilde{\beta}}\right) \tag{11}$$

Multiplication of FFNs:

$$\widetilde{\alpha} \otimes \widetilde{\beta} = \left(\mu_{\widetilde{\alpha}}\mu_{\widetilde{\beta}}, \sqrt[3]{v_{\widetilde{\alpha}}^3 + v_{\widetilde{\beta}}^3 - v_{\widetilde{\alpha}}^3 v_{\widetilde{\beta}}^3}\right) \tag{12}$$

The complement of FFN:

$$\mathrm{Com}(\widetilde{\alpha}) = (v_{\widetilde{\alpha}}, \mu_{\widetilde{\alpha}}) \tag{13}$$

Table 2 Linguistic terms

Linguistic Terms		FFNs	
		μ	v
Very Low	VL	0.1	0.75
Low	L	0.25	0.6
Medium Low	ML	0.4	0.5
Medium	M	0.5	0.4
Medium High	MH	0.6	0.3
High	H	0.7	0.2
Very High	VH	0.8	0.1

The WASPAS method [18, 29] is used to rank alternatives based on multiple criteria. It combines two well-known decision-making techniques: the Weighted Sum Model (WSM) and the Weighted Product Model (WPM) [30]. WSM calculates an alternative's total score by adding up weighted attribute values, making it easy to understand and apply. WPM takes a different approach by multiplying attribute values, giving more importance to strong attributes while penalizing weaker ones [31]. WASPAS has been further enhanced by incorporating fuzzy set extensions, making it adaptable to various decision-making problems [32]. Despite its effectiveness, WASPAS has limitations in accurately determining criteria weights when evaluating alternatives [33]. To overcome this, this study integrates BWM into WASPAS within a Fermatean Fuzzy environment, allowing for more precise weighting and improving decision accuracy in complex scenarios. This hybrid BWM-WASPAS model ensures a balanced and reliable evaluation by leveraging the strengths of both methods.

Step 1. Linguistic terms given in Table 2 are used to evaluate the alternatives.

In this framework, the assessment of alternative i with respect to criterion j by expert t is denoted by the corresponding FFN $A_{ij}^t = \left(\mu_{ij}^t, v_{ij}^t\right)$.

Step 2. Expert opinions are aggregated [28].

$$z_{ij} = Z(\mu_{ij}, v_{ij}) = \left(\sqrt[3]{1 - \prod_{t=1}^{d}\left(1 - \left(\mu_{ij}^t\right)^3\right)^{\psi^t}}, \prod_{t=1}^{d}\left(v_{ij}^t\right)^{\psi^t}\right) \tag{14}$$

where ψ^t is the expert weight.

Step 3. In the traditional WASPAS approach, a linear normalization technique is applied to the decision matrix. However, with FFSs, the elements are already within the 0 to 1 range, so adjusting the scale through normalization isn't necessary. For non-beneficial (cost) criteria, however, adjustments are needed. This study uses the complement of FFSs to adjust values associated with non-beneficial criteria. Equation (13) defines the complement of a FFN.

Step 4. The aggregated evaluations are then converted into crisp values using the score function [30].

$$S(z_{ij}) = \frac{1}{2}\left[\left(\left(\mu_{z_{ij}}\right)^3 - \left(v_{z_{ij}}\right)^3 - ln\left(1 + \left(\pi_{z_{ij}}\right)^3\right)\right) + 1\right] \tag{15}$$

Step 5. For each alternative, Q^1 (WSM) and Q^2 (WPM) are calculated based on the criteria weights and aggregated evaluations:

$$Q_i^1 = \sum_{j=1}^{n} w_j Z_{ij} \tag{16}$$

$$Q_i^2 = \prod_{j=1}^{n} Z_{ij}^{w_j} \tag{17}$$

Step 6. The values Q^1 and Q^2 each alternative is combined to determine the relative preference value.

$$Q_i = \lambda Q_i^1 + (1 - \lambda) Q_i^2 \tag{18}$$

λ is the threshold value.

Step 7. The crisp value of Q_i is calculated based on score function for each alternative i. Finally, the alternatives are ranked in descending order based on their crisp values.

4 Case study

This paper focuses on the determination of the best 3D printing technology for custom manufacturing. The proposed methodology integrates BWM with FF-WASPAS method with considering various criteria and alternative technologies. For this purpose, we determined nine main criteria, as defined in Table 3 with literature review and expert view. In this step, firstly, the opinions of a five-person expert team consisting of industrial engineering and mechanical engineering academicians were collected. In addition, similar studies in the literature on this field were examined and analyzed and the criteria given in Table 3 were determined. And, BWM is applied in order to calculate the criteria weights.

Then, we selected six 3D printing technologies based on expert opinions and literature review, as described in Table 4. The selection of the six 3D printing technologies analyzed in this study was based on their prominence and widespread application in the custom manufacturing industry. These technologies represent a diverse range of capabilities. Additionally, they are well-documented in the literature and extensively used across various industries such as healthcare, aerospace, automotive, and consumer goods,

Table 3 Definition of proposed criteria

Criteria	Definitions	References
C1. Cost	It covers the installation, operation, and maintenance costs of 3D printing technology	[2, 34]
C2. Precision and Surface Quality	It refers to the level of accuracy provided by the printing technology in the production process. High precision is especially important for parts that require detailed or precise measurements	[35, 36]
C3. Finishing Requirement	It refers to the additional processes that must be performed after printing in order for the produced part to reach the desired surface quality, durability, or dimensional accuracy	Expert view
C4. Production Speed	It indicates how long technology can produce a part. High production speed provides a significant advantage for time-sensitive projects	[12]
C5. Material Compatibility	It refers to the ability of 3D printing technology to work with different materials. Adapting to various materials allows technology to be used in a wide range of applications	[2]
C6. Functional Durability	It refers to the resistance of the produced part against mechanical and environmental conditions. Durability ensures that the part is long-lasting and reliable	Expert view
C7. Ability to Manufacture Complex Geometry	It refers to the ability of technology to produce complex and detailed geometries. This feature is especially important in productions that require special design or high detail	[2]

Table 3 (continued)

Criteria	Definitions	References
C8. Environmental Impact	It includes sustainability criteria such as energy consumption of technology, waste production, and environmental footprint. Low environmental impact is the reason for preference for environmentally friendly production	[2, 34, 37]
C9. Technological Maturity	It indicates the level of development of technology and the degree of acceptance in the industry. A mature technology may be preferred because it is more reliable and widely used	[2]

Table 4 Alternative 3D printing technologies

Alternatives	Description
Fused Deposition Modeling (FDM)	This method, which prints and shapes thermoplastic material layer by layer, offers an economical and fast solution. It is usually used for prototyping, but has low surface quality and precision limitations
Stereolithography (SLA)	SLA produces high-resolution parts by laser curing a photosensitive liquid resin. It is suitable for precise surface quality and intricate details, but it is costly and operates at lower speeds
Selective Laser Sintering (SLS)	In this method, the laser selectively combines the powdered material and creates strong, durable parts. Although it has wide material compatibility, the surface quality may not be smooth
PolyJet/Material Jetting	PolyJet, which produces high-precision parts with very thin layers, offers multiple color and material options. However, it may not be ideal for applications requiring functional durability due to limited material durability
Direct Metal Laser Sintering (DMLS)	This method, which produces metal parts by laser bonding metal powders, is preferred for industrial and durable parts. It is a high-cost and complex process, but provides exceptional durability and precision
Digital Light Processing (DLP)	Similar to SLA, DLP, a resin-based method, produces high-resolution parts using digital light projection. Although it provides high precision, the processing speed and material options may be limited

making them relevant for a comprehensive evaluation. The chosen alternatives also cover a broad spectrum of material types, providing a balanced comparison that reflects the needs of diverse manufacturing scenarios. The ranks of alternative technologies were calculated by mixing the criteria weights obtained with BWM into the FF-WASPAS method.

4.1 Calculation of criteria weights with BWM

In this section, the BWM is applied to determine the criteria weights. In this step, the weights of the criteria are calculated by identifying the best worst criterion, as evaluated by the 5 experts and offered in Table 5. The expert team consists of five academics in industrial engineering and mechanical engineering department.

Table 5 shows the most and the least important criteria. As an example, The E1 identifies C2 (Precision and Surface Quality) as the most important (best) criterion and C9 (Technological Maturity) as the least important (worst) criterion. Two of the experts evaluated *Functional Durability* as the most important criterion. For the least important criterion, two experts pointed out the *Cost* criterion, while two decided on *Technological Maturity.* After gathering expert views, both Best-to-Others and Others-to-Worst vectors are created as presented in Table 6.

E1 provides pairwise comparisons of the Best criterion (C2) to all other criteria and all other criteria to the Worst criterion (C9). These ratings are as follows:

- **Best-to-Others (B2O)**: [C1,C2,C3,C4,C5,C6,C7,C8,C9] = [2,1,3,4,4,5,2,6,7]
- **Others-to-Worst (O2W)**: [C1,C2,C3,C4,C5,C6,C7,C8,C9] = [5,6,4,4,4,4,6,2,1]

Using the comparison vectors, the mathematical model outlined in Step 1.5 was executed to determine the criteria

Table 5 The best and the worst criteria by experts

Expert	Best	Worst
E1	C2. Precision and Surface Quality	C9. Technological Maturity
E2	C6. Functional Durability	C9. Technological Maturity
E3	C6. Functional Durability	C3. Finishing Requirement
E4	C7. Ability to Manufacture Complex Geometry	C1. Cost
E5	C4. Production Speed	C1. Cost

Table 6 Decision vectors for criteria

Expert	Best-to-Others	Others-to-Worst
E1	2,1,3,4,4,5,2,6,7	5,6,4,4,4,4,6,2,1
E2	3,2,7,5,6,1,4,8,9	7,8,3,5,4,9,6,2,1
E3	5,4,6,5,2,1,3,3,3	4,2,3,2,4,5,3,2,3
E4	1,7,8,5,3,6,9,4,2	1,7,8,5,3,6,9,4,2
E5	9,1,2,1,4,3,1,4,3	1,8,6,9,6,5,8,4,5

weights. Subsequently, the experts' evaluations were analyzed for consistency, and all were confirmed to be consistent. The BWM procedure was then applied to calculate the criteria weights for each expert, with the resulting weights presented in Table 7.

As shown in Table 7, Expert 1 (E1) identified C2 (Precision and Surface Quality) as the most important criterion, assigning it a weight of 0.2581. Conversely, the least important criterion, C9 (Technological Maturity), was assigned a weight of 0.0323. In this study, we assumed equal weights for all experts when aggregating their evaluations. This assumption was made to ensure fairness and consistency, as all experts were selected based on their equivalent level of expertise and knowledge of the problem domain. Equal weighting reflects the absence of any pre-defined hierarchy or differences in reliability among the experts. The final aggregated weights, derived from the experts' evaluations, are summarized in Table 8.

Table 8 Final criteria weights

	Weight	Rank
C1. Cost	0.0870	7
C2. Precision and Surface Quality	0.1603	1
C3. Finishing Requirement	0.0809	9
C4. Production Speed	0.1078	5
C5. Material Compatibility	0.1106	4
C6. Functional Durability	0.1443	2
C7. Ability to Manufacture Complex Geometry	0.1245	3
C8. Environmental Impact	0.0816	8
C9. Technological Maturity	0.1029	6

According to Table 8, the most important criterion in selecting 3D printing printer technology for custom manufacturing is *Precision and Surface Quality* with a weight of 0.1603 while the least important criterion is *Finishing Requirement* with a weight of 0.0809. The second most important criterion was determined as *Functional Durability* with 0.1443.

4.2 Ranking of alternative 3D printing technologies with FF-WASPAS method

In this stage, the scores of alternative technologies are determined with integrating the criteria weights obtained by BWM into the FF-WASPAS method. For this purpose, seven different 3D printing technologies, presented in Tablo 4, were evaluated by the proposed approach.

Table 7 Criteria weights for each expert

	E1	E2	E3	E4	E5
C1. Cost	0.1613	0.1277	0.0710	0.0573	0.0178
C2. Precision and Surface Quality	0.2581	0.1915	0.0888	0.0736	0.1897
C3. Finishing Requirement	0.1075	0.0547	0.0592	0.0644	0.1186
C4. Production Speed	0.0806	0.0766	0.0710	0.1031	0.2075
C5. Material Compatibility	0.0806	0.0638	0.1775	0.1718	0.0593
C6. Functional Durability	0.0645	0.3146	0.1775	0.0859	0.0791
C7. Ability to Manufacture Complex Geometry	0.1613	0.0958	0.1183	0.0573	0.1897
C8. Environmental Impact	0.0538	0.0479	0.1183	0.1289	0.0593
C9. Technological Maturity	0.0323	0.0274	0.1183	0.2577	0.0791

Table 9 Criteria-alternative assessment

		C1	C2	C3	C4	C5	C6	C7	C8	C9
E1	Fused Deposition Modeling (FDM)	L	L	M	MH	MH	MH	ML	M	MH
	Stereolithography (SLA)	H	H	H	L	MH	M	MH	ML	M
	Selective Laser Sintering (SLS)	VH	H	H	MH	MH	M	H	M	L
	PolyJet/Material Jetting	MH	H	H	H	H	L	H	M	H
	Direct Metal Laser Sintering (DMLS)	H	VH	VH	MH	MH	H	MH	MH	M
	Digital Light Processing (DLP)	MH	H	H	MH	MH	M	H	M	M
E2	Fused Deposition Modeling (FDM)	VL	VL	VL	L	VH	M	VL	VH	VH
	Stereolithography (SLA)	MH	MH	H	ML	ML	L	M	M	H
	Selective Laser Sintering (SLS)	L	L	L	M	H	MH	VH	H	MH
	PolyJet/Material Jetting	H	VH	M	H	M	ML	H	L	M
	Direct Metal Laser Sintering (DMLS)	VH	ML	VH	VL	MH	VH	MH	VL	L
	Digital Light Processing (DLP)	M	M	ML	VH	L	VL	L	MH	VL
E3	Fused Deposition Modeling (FDM)	VL	ML	ML	H	M	L	MH	M	H
	Stereolithography (SLA)	L	VH	MH	L	MH	M	VH	ML	H
	Selective Laser Sintering (SLS)	M	M	M	M	H	H	H	M	MH
	PolyJet/Material Jetting	MH	H	MH	M	ML	L	VH	H	M

Table 9 (continued)

		C1	C2	C3	C4	C5	C6	C7	C8	C9
	Direct Metal Laser Sintering (DMLS)	VH	VH	H	L	H	VH	H	MH	H
	Digital Light Processing (DLP)	H	H	MH	ML	ML	ML	H	M	H
E4	Fused Deposition Modeling (FDM)	L	ML	M	VL	H	M	VH	M	M
	Stereolithography (SLA)	VH	VH	VH	M	M	MH	VH	M	H
	Selective Laser Sintering (SLS)	VH	M	M	MH	ML	VH	VH	M	MH
	PolyJet/Material Jetting	MH	M	M	MH	M	ML	MH	M	M
	Direct Metal Laser Sintering (DMLS)	VH	VH	MH	VH	MH	VH	MH	M	MH
	Digital Light Processing (DLP)	H	H	H	M	M	ML	MH	M	M
E5	Fused Deposition Modeling (FDM)	M	ML	M	MH	M	M	M	ML	MH
	Stereolithography (SLA)	M	VH	VH	ML	ML	ML	VH	H	MH
	Selective Laser Sintering (SLS)	H	M	L	MH	VH	MH	H	ML	MH
	PolyJet/Material Jetting	MH	MH	VH	M	M	L	MH	ML	ML
	Direct Metal Laser Sintering (DMLS)	VH	MH	ML	ML	H	VH	ML	ML	ML
	Digital Light Processing (DLP)	MH	VH	VH	ML	ML	ML	VH	H	MH

Firstly, a decision matrix is created that facilitates its evaluation using the linguistic terms given in Table 2. The FF-WASPAS method supports the decision-making process for a comprehensive and precise evaluation of alternatives, taking into account multiple criteria and their respective importance. And the criteria-alternative assessment for each expert is offered in Table 9.

Secondly, to rank the alternatives, with the aggregated values, Q_j were calculated, and the alternatives were ranked in descending order, as exposed in Table 10. Here, λ is set to 0.5 to combine the weighted sum and weighted product models.

According to the results, *Stereolithography (SLA)* was determined as the best 3D printing technologies for custom manufacturing. Second was *Direct Metal Laser Sintering (DMLS)* and the lowest score compared to other alternatives was *Fused Deposition Modeling (FDM)*.

4.3 Sensitivity analysis

In this section, we perform a sensitivity analysis by varying the threshold value (λ) in the FF-WASPAS methodology to investigate its impact on the scores and rankings of the alternatives. The threshold value λ determines the weight given to WSM and the WPM within the WASPAS framework. The analysis was conducted using threshold values ranging from 0 to 1, with increments of 0.1. The scores and rankings obtained for each alternative at different threshold values are presented in the results. The scores for each alternative across the threshold values are summarized in Table 11.

Table 11 reveals how the preferences change as the threshold value shifts between the two components of the WASPAS method. For better interpretation of the ranking dynamics, Fig. 3 illustrates the rankings derived from these scores for all alternatives as the threshold value is adjusted.

The highest score across all thresholds is consistently achieved by *Stereolithography (SLA)*, making it the top-ranked alternative for all threshold values. This indicates its robustness and dominance across varying levels of weighting between WSM and WPM. The ranking graph shows that *Selective Laser Sintering (SLS)* and *Direct Metal Laser Sintering (DMLS)* compete closely for the second position. However, as the threshold increases, their relative rankings stabilize, with DMLS consistently occupying the second position for thresholds above 0,5. *Digital Light Processing (DLP)* is ranked last across all threshold values, highlighting its comparatively weaker performance in this study.

The consistency of SLA as the top-ranked alternative across all threshold values indicates its suitability for industries prioritizing precision, surface quality, and the ability to handle complex geometries. This makes SLA particularly appealing for sectors such as healthcare and aerospace, where detailed and reliable outputs are critical. On the other hand, DMLS consistently ranks second in most scenarios, making

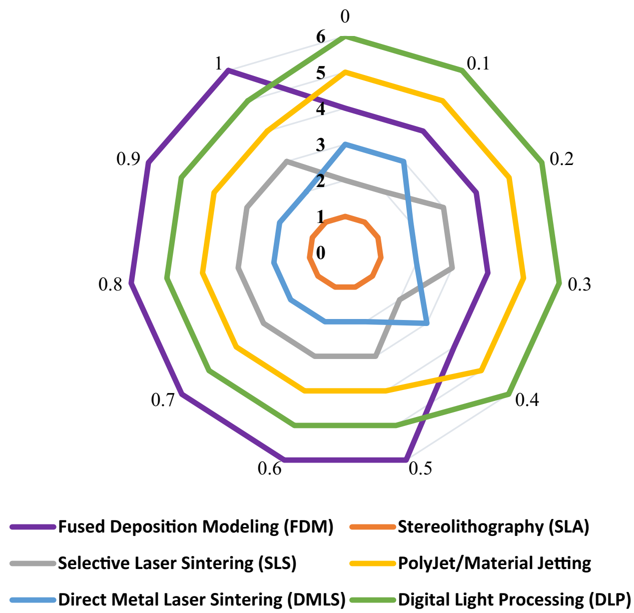

Fig. 3 Ranking of alternatives according to sensitivity analysis

it ideal for industries such as automotive and heavy machinery, where functional durability and material strength are of paramount importance. SLS, which shows competitive scores and ranks close to DMLS, is well-suited for applications that require material versatility, such as prototyping or small-scale production in consumer goods. Lower-ranked technologies, such as FDM and PolyJet/Material Jetting, may still be valuable for industries with lower precision requirements or limited budgets, such as rapid prototyping or small-batch manufacturing.

The stability of the rankings under sensitivity analysis highlights the robustness of the proposed methodology, even with varying λ values. For decision makers, regardless of the weight distribution between WSM and WPM, top-ranked alternatives such as SLA remain reliable choices. However, as λ shifts, its emphasis changes-higher values prioritize overall balanced performance, while lower values penalize weaknesses in specific criteria. This flexibility ensures alignment with organizational goals and constraints, allowing decision makers to tailor the methodology to their priorities.

4.4 Comparative analysis

To validate and cross-check the robustness of the proposed methodology, we compared them with rankings obtained using the Fermatean Fuzzy TOPSIS (FF-TOPSIS) method. FF-TOPSIS was selected for this comparison due to its ability to effectively capture the degree of hesitation in decision-makers' preferences, offering a comprehensive evaluation under uncertainty. In the TOPSIS method, it is certain that the best solution is the one that comes closest to the ideal

Table 10 Scores and ranks of alternatives

	Weighted sum	Weighted product	Score	Rank
Fused Deposition Modeling (FDM)	0.487	0.229	0.358	6
Stereolithography (SLA)	0.6412	0.2467	0.4439	1
Selective Laser Sintering (SLS)	0.5784	0.2459	0.4121	3
PolyJet/Material Jetting	0.5361	0.2064	0.3713	4
Direct Metal Laser Sintering (DMLS)	0.6034	0.2416	0.4225	2
Digital Light Processing (DLP)	0.5245	0.2032	0.3638	5

Table 11 Results of the sensitivity analysis

	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Fused Deposition Modeling (FDM)	0.229	0.255	0.281	0.306	0.332	0.358	0.384	0.410	0.435	0.461	0.487
Stereolithography (SLA)	0.247	0.286	0.326	0.365	0.361	0.444	0.483	0.523	0.562	0.602	0.641
Selective Laser Sintering (SLS)	0.246	0.279	0.312	0.346	0.356	0.412	0.445	0.479	0.512	0.545	0.578
PolyJet/Material Jetting	0.206	0.239	0.272	0.305	0.315	0.371	0.404	0.437	0.470	0.503	0.536
Direct Metal Laser Sintering (DMLS)	0.242	0.278	0.314	0.350	0.335	0.422	0.459	0.495	0.531	0.567	0.603
Digital Light Processing (DLP)	0.203	0.235	0.267	0.300	0.298	0.364	0.396	0.428	0.460	0.492	0.524

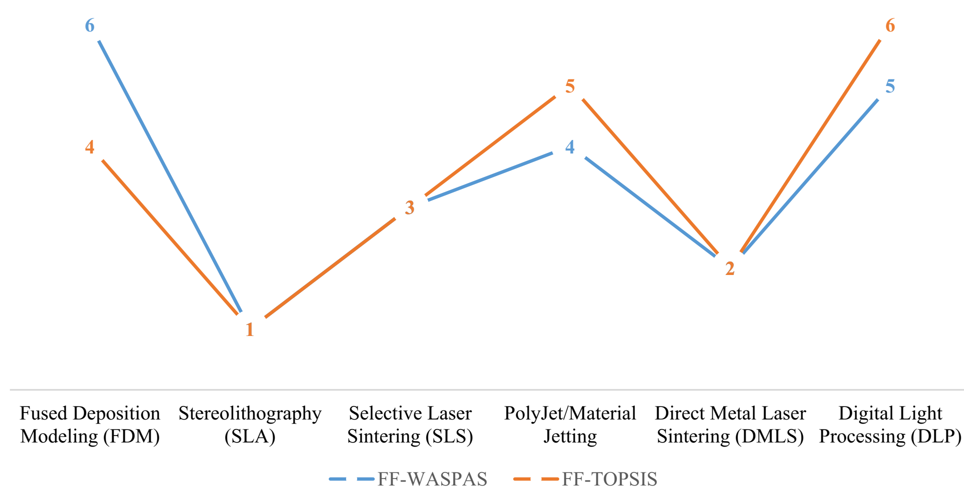

Fig. 4 Ranking for comparative analysis

solution. Additionally, the further it moves away from the negative ideal solution, the more favorable it becomes [38]. The use of FF-TOPSIS allows for a deeper analysis under uncertainty and enhances decision-making by addressing hesitation in the evaluations. This complements WASPAS by introducing an additional layer of confidence in the robustness of the rankings. The steps for FF-TOPSIS were implemented following the methodology provided in [39]. The final scores and from both methods are summarized in Table 12, while Fig. 4 provides a visual comparison of the ranking.

Both WASPAS and FF-TOPSIS identified SLA as the top-performing alternative. This alignment highlights the robustness of SLA across different evaluation methodologies. Variations were observed in the rankings for FDM and PolyJet/Material Jetting. While WASPAS ranked FDM as the least preferred alternative, FF-TOPSIS placed it fourth. This

Table 12 Results of both FF-WASPAS and TOPSIS

	FF-WASPAS	FF-TOPSIS
Fused Deposition Modeling (FDM)	0.3580	0.4214
Stereolithography (SLA)	0.4439	0.5591
Selective Laser Sintering (SLS)	0.4121	0.5392
PolyJet/Material Jetting	0.3713	0.3694
Direct Metal Laser Sintering (DMLS)	0.4225	0.5486
Digital Light Processing (DLP)	0.3638	0.3451

suggests that FDM's performance may be sensitive to the specific criteria weighting and aggregation method used.

The discrepancies between the two methods can be attributed to differences in how the methods handle trade-offs among criteria. FF-WASPAS combines the weighted scores through a linear mechanism, whereas FF-TOPSIS leverages relative closeness to the ideal solution, which can amplify differences in alternative performance. While the rankings for most alternatives remain consistent between the two methods, discrepancies are observed for Fused FDM and PolyJet/Material Jetting. Specifically, FDM ranks sixth in WASPAS but improves to fourth in FF-TOPSIS, while PolyJet shifts from fourth in WASPAS to fifth in FF-TOPSIS. These differences highlight the sensitivity of these alternatives to the aggregation mechanisms of the two methods. For FDM, the discrepancy can be attributed to the FF-TOPSIS method's emphasis on relative closeness coefficients, which may prioritize specific criteria, where FDM performs comparatively better. In contrast, WASPAS penalizes its lower scores in other critical criteria. Similarly, for PolyJet, FF-TOPSIS appears to prioritize its weaknesses, such as limited functional durability, more strongly, resulting in a lower ranking. These variations highlight the importance of selecting the appropriate decision-making framework based on the specific context and priorities of the application.

5 Discussion

This study suggests a methodical approach to selecting the best 3D printing technology for custom manufacturing by considering various criteria. The results highlight the importance of the following criteria in the selection process: *C2. Precision and Surface Quality, C6. Functional Durability, and C7. Ability to Manufacture Complex Geometry*. In contrast, *C3. Finishing Requirement* is determined to be the least important criterion compared to the other criteria. When considering the custom manufacturing process, it is expected that precision and surface quality are very important. Therefore, this criterion should be taken into consideration significantly when choosing 3D printing in this sector. Also, the purpose of the additive manufacturing of models is to ensure continuity to create a product with high surface quality [39]. In addition, hybrid production approaches such as combining 3D printing with traditional subtractive machining can be used to achieve higher precision and surface quality in this process.

Precision and surface quality emerged as the most important criterion, reflecting its critical role in determining the overall utility and aesthetics of 3D-printed products. Achieving high precision and smooth surfaces is essential in custom manufacturing, where unique product specifications often require exceptional detail [40]. The superior quality of the surface finish minimizes the need for extensive post-processing, saving time and resources while ensuring customer satisfaction. Precision directly affects the functionality and reliability of the final product in industries such as medical devices and aerospace, where precise specifications are critical.

Functional durability ranked as the second most important criterion, highlighting the need for robust and durable components in custom manufacturing. In applications that require high performance under varying environmental and operating conditions, such as automotive and industrial tooling, durability is especially important [41]. In line with sustainability goals, a durable product not only extends the life of the manufactured part, but also reduces maintenance and replacement costs. Choosing a 3D printing technology that ensures strength and durability is paramount to maintaining customer confidence and achieving economic efficiency, given the increasing demand for parts that balance innovation with reliability. However, there are also studies focusing on design to increase durability and functionality, especially in the field of building, to prevent disinformation [42]. Similarly, 3D printing of concrete is widely used to produce new structural sections with numerous benefits, and new approaches to improving durability have been proposed [43]. The ability to produce complex geometries is identified as the third most important criterion. This emphasizes its importance in unlocking the full potential of custom manufacturing. 3D printing is often credited with enabling intricate designs not possible with traditional manufacturing methods, allowing for greater innovation and design freedom [44]. In sectors such as healthcare, where custom implants or prosthetics with complex geometries are often required, this capability is particularly important.

Among the evaluated technologies, SLA was selected as the best alternative 3D printing technology for custom manufacturing. SLA produces parts with particularly high resolution and precise surface quality. It is also suitable for parts with complex details. In this case, SLA produces based on criteria determined as very important for the 3D printing technology selection process for custom manufacturing. SLAs are also frequently used in areas such as tissue engineering. They are also preferred for the production of dosage forms that encapsulate unstable drugs due to their versatility and solubility benefits [45]. In addition, it is also preferred in drug-loaded product and medical device production processes because it allows objects to be produced at room temperature and thus reduces the risk of deterioration [46]. In particular, 60% of experts evaluated this alternative as 'very high' in terms of the *C2. Precision and Surface Quality* criterion. Conversely, FDM was determined the least favorable alternative, mainly due to its inferior performance in this criterion. In addition, DMLS was determined as the second-best alternative technology. Although this alternative has many strengths, 80% of the experts evaluated this alternative as 'very high' in terms of *C1. Cost* criterion and 20% as 'high'. In addition, according to the evaluations, it is not strong in terms of *C9. Technological Maturity* criterion.

The results of this analysis indicated that SLA outperformed other technologies in terms of precision and surface finish, which are critical factors for custom manufacturing applications [47]. The expert-driven evaluation process confirmed that SLA is the most suitable 3D printing technology for custom manufacturing, particularly when high precision and superior surface finish are required. SLA's superior performance in these criteria aligns with its well-documented advantages in the literature, such as exceptional precision and surface finish, making it particularly suitable for applications demanding high-quality outputs. While other technologies, such as FDM and SLS, offer advantages in terms of material versatility and production speed, they fall short in meeting the stringent quality requirements of custom manufacturing [48]. The use of expert opinions, combined with the rigorous application of BWM and FF-WASPAS, provided a solid foundation for our conclusion. This approach aligns with recent studies that emphasize the importance of expert judgment in decision-making processes involving complex technological evaluations [19].

The selection of SLA as the most suitable 3D printing technology for custom manufacturing demonstrates the effectiveness of the proposed methodology and proves its capability to assess and rank alternatives with precision. These findings highlight the critical role of precision, surface quality and durability in the selection process of 3D printing technology in custom manufacturing. And also, the results highlight the need for careful consideration of these factors in particular for the selection of a 3D printer that meets the production requirements for custom manufacturing with precision. Thus, this study provides guidance to company managers and stakeholders by providing a comprehensive evaluation process. And, sensitivity analysis further validated the effectiveness of the proposed methodology and showed that this methodology is adaptable and reliable in various decision-making scenarios. The consistent ranking of the SLA alternative as the best alternative regardless of coefficient changes strengthens the suitability of the selected alternative.

6 Conclusion

The purpose of this study is to address the critical need for the selection of the most appropriate 3D printing technology for custom manufacturing, a field that requires precision, adaptability, and efficiency. Through a novel integration of BWM criteria weighting and FF-WASPAS alternatives ranking, the research aimed to provide a systematic and comprehensive evaluation framework. In addition to identifying best 3D printing technology among six prominent options, this study aim to establish a decision methodology that could balance multiple considerations, including cost, accuracy, environmental impact, and technological sophistication.

The study identifies stereolithography (SLA) as the most suitable 3D printing technology for custom manufacturing, consistently ranking highest among all methods evaluated. Precision and Surface Quality (C2) emerges as the most critical factor, reflecting the importance of accuracy and finish in custom manufacturing applications. Functional Durability (C6) ranks second, emphasizing the need for robust and reliable components, while Ability to Manufacture Complex Geometry (C7) isidentified as the third most important criterion, highlighting the value of design flexibility in meeting unique customer requirements. The results underscore SLA's ability to excel in these areas, making it the preferred choice for applications requiring intricate designs, superior quality and long-term reliability. These results align with the practical needs of industries seeking to optimize their manufacturing processes for custom products.

The main contributions of this study: (i) the most suitable 3D printing technology for custom manufacturing by using a novel hybrid MCDM approach was selected by considering a detailed criteria set, (ii) for the first time in the literature, BWM and FF-WASPAS methods within the fuzzy environment are integrated, (iii) the novel methodology is included in the decision-making literature, filling a gap by providing a robust tool for handling uncertainty in multi-criteria valuations to confirm the sustainability and efficiency of the custom manufacturing process.

For practitioners and decision makers in the custom manufacturing industry, the results of this study provide valuable guidance. The study identifies stereolithography (SLA) as the most suitable 3D printing technology, highlighting its ability to deliver the high precision, robust longevity, and complex design capabilities required to meet the demands of modern manufacturing. The multi-criteria decision framework presented in this study enables manufacturers to make informed choices that align with their strategic objectives by providing a systematic approach to evaluating technologies based on diverse factors such as cost, environmental impact, and material compatibility. Furthermore, the insights gained from prioritizing criteria such as precision and durability can help industries optimize their operations, reduce manufacturing inefficiencies, and improve product quality, ultimately helping to compete in a rapidly evolving marketplace.

While integrating BWM with FF-WASPAS provides a robust framework, certain challenges and limitations were encountered. A key challenge is the computational complexity associated with the Fermatean fuzzy environment, which requires the handling of three interdependent membership parameters—membership, non-membership, and hesitancy—while maintaining their constraints. This increases the analytical workload compared to traditional crisp or intuitionistic fuzzy sets. In addition, BWM relies heavily on the consistency of expert judgments, particularly in determining the best and worst criteria. Any inconsistency in these pairwise comparisons can propagate through the FF-WASPAS ranking process. This can potentially affect the reliability of the results. Despite these challenges, the benefits of this integration, such as improved handling of uncertainty and increased decision accuracy, outweigh its limitations. Future work could explore strategies for simplifying the computations, such as using more efficient algorithms or automating certain stages of the process, to make the framework more accessible for practical applications.

In future studies, different fuzzy-based MCDM methods that can be applied for more comprehensive criteria and alternatives can be considered and the results found can be compared with the results of this study. The proposed method can be used in different problems such as material selection for 3D printing process. In addition, including stakeholder perspectives such as company managers and/or customers in the field of study can increase the power of the analysis. Moreover, the proposed methodology can be practically applied to different problems in different fields and provide effective solutions.

Data availability The data are available upon request to the corresponding author (*).

Declarations

Conflict of interest All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript. 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.

Consent for publication The authors confirm that the final version of the manuscript has been reviewed, approved and consented for publication by all authors.

Ethical approval.

Ethics committee approval is not required.

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