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Research article

Assessment of consolidative multi-criteria decision making (C-MCDM) algorithms for optimal mapping of polymer materials in additive manufacturing: A case study of orthotic application

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A R T I C L E I N F O

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Multi-criteria decision making
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CRITIC
Integrative weights
Simple ranking process

A B S T R A C T

Objective: The objectives of this research are twofold. The primary goal is to introduce, investigate, and contrast consolidative multi-criteria decision-making (C-MCDM) approaches. The second objective is the investigation of five alternative additive manufacturing materials.
Methods: It integrates the subjective and objective weights using the Bayes hypothesis in conjunction with a normal method. Chang's Extent Analysis Method under fuzzy logic is used to estimate subjective weights and the CRITIC approach is used for assessing objective weights. Ranking techniques, including the simple ranking process (SRP), multi-objective optimization based on ratio analysis (MOORA), measurement alternatives and ranking according to compromise solution (MARCOS), and technique for order preference by similarity to ideal solution (TOPSIS) are applied. It also encompasses sensitivity analysis based on Kendall's coefficient of concordance and rank reversal phenomenon analysis. Spearman's rank correlation coefficient, a weighted rank measure of correlation, and rank similarity coefficient are among the metrics used to evaluate agreement between different approaches. It entails gathering expert opinions regarding the importance of various criteria as well as conducting extensive experiments.
Results: The findings of the study indicate that polylactic acid is the best material to use for orthoses. When compared to the other MCDM approaches being discussed, SRP is the most reliable approach. It is also demonstrated that the SRP, MARCOS, and TOPSIS methods are rank reversal-free. Furthermore, SRP exhibits a very poor association with the TOPSIS technique but a strong correlation with the MOORA and MARCOS approaches.
Conclusions: To ensure results reliability, it is necessary to consider both the subjectivity and objectivity of weights as well as apply multiple MCDM methodologies in addition to sensitivity analysis.

1. Introduction

Osteoarthritis (OA) is a chronic and progressive disease affecting the joints. The condition elicits sensations of discomfort, inflammation, and limited range of motion, hence impeding an individual's capacity for unrestricted movement. The prevalence of this

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condition is highest in the knee joints. It is a significant health issue, as evidenced by its ranking as the eleventh most prevalent cause of worldwide disability [1]. There are several variables that influence the development of OA. Some of the conditions that could lead to the onset of joint injury or stress include a prior history of such injuries, advanced age, and being overweight [2]. Women are disproportionately affected compared to males [3]. The prevalence of OA tends to be higher among those in older age groups, with around 70 % of cases occurring in individuals aged 55 and above [4]. Consequently, as populations continue to age, it is anticipated that the worldwide incidence of OA will rise. OA often manifests in individuals between the ages of late 40s to mid-50s, however, it may also impact younger individuals, such as athletes or those who have joint damage or trauma [5]. Additionally, it serves as a prominent motive for seeking medical advice in both primary and specialized healthcare settings. According to the World Health Organization, the cosmopolitan prevalence of OA has reached around 528 million individuals, reflecting a substantial rise of 113 % since 1990 [6,7]. Patients diagnosed with OA affecting the knee joint may receive treatment in the form of a knee brace known as knee orthosis.

An orthosis is a medical apparatus employed to augment the physiological capabilities of the human body. The primary objective of knee orthosis is to alleviate knee discomfort, enhance physical functionality, and impede the advancement of the underlying condition [8]. The utilization of these devices has the potential to decrease symptoms, enhance functionality, and even enhance the overall quality of life for patients. The existing prefabricated orthoses, and support accessories, are inadequate in terms of comfort and customized support. As a result, these devices provide a significant constraint on the effectiveness of treatment. While custom-created orthoses that are tailored to the explicit demands of a user have shown greater rates of success, the conventional manufacturing process is characterized by labor-intensive and time-consuming manual labor, resulting in a limited degree of personalization [9]. The production of orthoses by conventional manufacturing techniques necessitates the acquisition of precise anatomical measurements, which must be carried out by a qualified medical professional. In instances when a greater degree of customization is necessary for the use of orthoses, the fabrication of plaster casts of the affected limb is undertaken. The production process of these molds is characterized by its intense nature, requiring significant labor effort and resulting in substantial material waste [10].

In contrast to conventional fabrication, three-dimensional (3D) printing also referred to as Additive manufacturing (AM) is a highly suitable technology for achieving mass customization with accurate fitting and has the potential to significantly reduce labor-intensive processes. The efficacy of 3D printing has been shown in its ability to swiftly and economically produce customized orthoses, as well as its capacity to bring about significant improvements in service provision. The use of AM technology enables enhanced manufacturing capabilities, reduced time to market, and facilitates the customization of products [11]. This advancement leads to several benefits, including improved comfort and aesthetics, as well as the ability to monitor growth. Among AM technologies, Fused Deposition Modelling (FDM) is well recognized as a prevalent technique that can fabricate objects by a process involving the application of heat and the extrusion of a thermoplastic filament, which is deposited in successive layers. FDM is widely recognized as a globally embraced technology for the AM of orthotic devices due to several factors [12]. These factors include the widespread availability of cost-effective and easily obtainable 3D printers, the affordability of raw materials, the simplicity of equipment and material management, and the ability to produce lighter and more durable products. Despite the enormous promise and various advantages, it brings, FDM implementation for orthoses is not straightforward. One of the main problems with FDM is the material choice for orthoses. It is attributed to several conflicting selection criteria for materials, namely price, weight, biocompatibility, biodegradability, durability, and mechanical properties [13]. Consequently, careful material selection is crucial while creating an orthotic device using FDM. The selection of the optimal material for orthosis can only be achieved through the application of a methodical and organized mathematical methodology. The efficient solution of material selection instances with numerous non-commensurable and competing considerations is the deployment of the multi-criteria decision-making (MCDM) methods.

Orthoses being a non-drug and non-surgical treatment is often favored by the doctors and their OA patients. But, to fully utilize and reap the benefits of orthoses, it is crucial to design them with a number of factors in mind, such as cost, choice of materials, performance, weight, design customization, fabrication process, etc. Nowadays, 3D printing is the most popular technique for realizing orthoses since it can produce complicated, personalized shapes quickly and easily without the need for extra fixtures or tools. However, when using 3D printing for orthoses, deciding on the adequate material constitutes the most important factor since it affects many design characteristics, including user comfort, fitting, device cost, printing complexity, strength, etc. When identifying a material for 3D printing orthoses, customers are frequently perplexed by the abundance of options available to them. Likewise, users are confounded about which MCDM methods to choose and apply for a given selection problem due to the plethora of MCDM methods in the literature and the ongoing advancement of new MCDM methods by researchers. There are various approaches, including subjective and objective weight calculations, as well as a variety of ranking techniques that may yield multiple outcomes. Therefore, it is critical to acquaint users with the proper methodology for executing MCDM approaches efficiently, as well as how to assess their plausibility and gauge various MCDM outcomes. So, the primary focus of this research has been to provide a framework that enables users to compare as well as assess the performance and efficacy of various MCDM techniques in addition to identifying the optimal material for 3D printing orthoses.

This study is primarily concerned with investigating two aspects: choosing the appropriate material for orthoses and evaluating various MCDM techniques. There are two key objectives for the work. The first objective is to implement and evaluate consolidative MCDM (C-MCDM) methods. They are referred to as C-MCDM in this work because consolidative weights constitute the basis for the MCDM approaches' ranking. It entails applying Bayes theory and the normal technique to consolidate the subjective and objective weights. Any MCDM ranking procedure's effectiveness is contingent upon the accuracy of the criteria weight estimation. There are two methods for figuring out the criteria's weights. One method of weighting is known as the subjective technique since it involves obtaining weights with the assistance of experts. These weights are useful since they represent the views of highly knowledgeable professionals with a wealth of experience, however they may be biased. Conversely, certain weights are determined by the criteria values or the information in the data. These weights are referred to as objective weights. Although these weights are impartial, they do not reflect the preferences of stakeholders. This work therefore combines two weights utilizing two approaches, i.e., the standard approach and the Bayes theorem, to overcome the limits of the two methods and incorporate their benefits. The Chang's Extent Analysis Method under fuzzy logic (CEA-FL), which can handle imprecision in decision-making and characterize ambiguous data, is the subjective weighting approach employed in this work. The goal is to provide the most accurate interpretation of the criteria's weights. The CRiteria Importance Through Intercriteria Correlation (CRITIC) method is the objective approach that is employed since it is predicated on the inherent knowledge of the criteria and produces unbiased results. Various ranking techniques, such as the Simple Ranking Process (SRP), Multi-Objective Optimization based on Ratio Analysis (MOORA), Measurement alternatives and ranking according to compromise solution (MARCOS), and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), are used and examined to find the appropriate material or rank the different materials. A noteworthy feature of this work is the application of SRP, as documented in Ref. [14], one of the newest MCDM techniques with a distinct mathematical foundation. Sensitivity analysis based on Kendall's coefficient of concordance (SE-KC) and rank reversal instances is employed to evaluate the effectiveness of various ranking strategies. Several correlation indices, including Spearman's rank correlation coefficient (SRC), the weighted rank measure of correlation (WRC), and the rank similarity coefficient (RSC), are also used to compare the various C-MCDM techniques with one another.

The second objective is to investigate five alternative materials: polylactic acid (PLA), acrylonitrile butadiene styrene (ABS), Polyethylene terephthalate glycol (PETG), thermoplastic polyurethane (TPU), and Polypropylene (PP) using ten meticulously established criteria that capture the core facets essential for the AM of orthoses. Numerous factors pertaining to mechanical, physical, and user-related attributes are considered. Mechanical parameters namely tensile strength, yield strength, compression strength, elongation at break, and yield strength ratio are assessed experimentally using the universal testing machine. Physical experiments are used to measure tangible qualities, such as the shrinkage factor and water absorption. The additional quality attributes—such as biocompatibility, cost, and ease of printing—are gathered through online sources and printing experience. Additionally, it involves getting expert input on the significance of different criteria, which is necessary for evaluating subjective weights.

The work is divided into seven sections. Section 1 introduces the problem and objectives, while section 2 reports the literature. The MCDM approaches are discussed in section 3 and the data collection strategy is illustrated in Section 4. The utilization of the C-MCDM for the identification of AM polymer material for orthotic application is shown in Section 5. In section 6, the results of the material selection problem are presented together with an analysis of the C-MCDM methods. The outcomes of this work are concluded in the final section 7.

2. Literature survey

The fundamental criteria for designing an orthosis are its simplicity, lightness, durability, and user-friendliness. In orthosis design or orthotic applications, it is crucial to consider many key factors, including but not limited to weight, flexibility, practical usage, cost, and durability as seen in Fig. 1.

Orthoses may be classified into two categories: custom-made or prefabricated [16]. Prefabricated orthoses are readily available in standardized sizes, and frequently need adjustments to adequately conform to the user's anatomical structure and specific requirements. Prefabricated orthoses are characterized by their lower cost and easily accessible off-the-shelf goods [17]. These traditional custom-made orthoses are fabricated using plaster casts obtained from the patient's lower leg. This technique involves the use of plaster fluid to occupy the void left by the patient's cast, resulting in the formation of a constructive model [18]. This model is

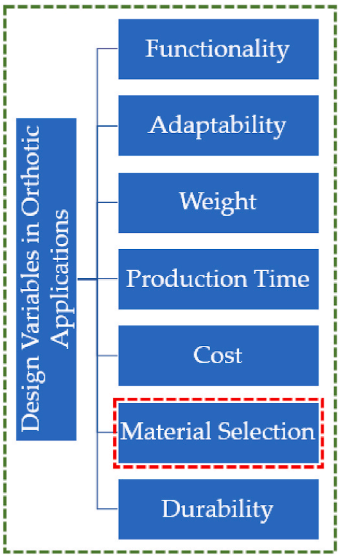

Fig. 1. Key factors in the orthosis design [15].

thereafter subject to human adjustments by the addition or removal of plaster. The positive model is altered and replicated to resemble the patient's leg and foot. This replica is then subjected to vacuum-forming using a thermoplastic polymer, resulting in the production of an orthosis. Nonetheless, the fabrication of the mold and the subsequent production of the final product include a time-consuming and intricate procedure, demanding significant investment of the technician's time in the construction of an orthosis. Additionally, this process may generate surplus waste materials. The duration of this procedure might vary from a minimum of two days to several weeks, depending upon the extent of postprocessing that is necessary. In contrast, personalized (or custom-made) orthoses exhibit superior conformity to the patient's anatomical structure and demonstrate enhanced performance compared to prefabricated orthotic devices [16]. According to research conducted at the prosthetic care facility, it was found that the primary determinant of satisfaction among orthosis users is their level of fitness [19].

The manufacturing process, design elements, and the materials used have a substantial impact on the efficacy and performance of an orthosis [16]. Improved production processes and the utilization of higher-quality materials can limit amputee risks and lower maintenance costs while simultaneously enhancing the fitting and usefulness. The material type of an orthotic device ultimately dictates its physical qualities, including adaptability, resilience, endurance, hardness, weight, and temperature tolerance [20]. However, selecting a material for orthotics should not be based just on one feature of the product's design. For example, if a material is chosen primarily on its durability, there exists a significant likelihood that the anticipated biomechanical efficacy and desired level of comfort won't be achieved. The choice of materials and the ultimate product design are contingent upon the manufacturing method. Therefore, it is crucial to acknowledge the particular materials that are suitable for AM. Researchers utilize a diverse range of materials for knee orthosis applications, each possessing distinct merits and drawbacks. To address this issue, it is crucial to carefully consider the application of the appropriate material for a knee orthosis. Materials including PLA, ABS, TPU, etc., are commonly utilized in the production of 3D-printed orthoses. Because PLA is devoid of heavy metals and environmental hormones, it is a sustainable polymer with positive environmental traits. Furthermore, it is important to highlight that PLA has noteworthy qualities in terms of its biocompatibility and renewability [21]. ABS is a type of styrene resin that is composed of three different components. Prominent

Table 1
MCDM methods and their applications in material selection.

Author (s)	Application	MCDM method (s)
Jha et al. [40]	Material selection for biomedical applications, namely prosthetics or orthotics	TOPSIS
Agrawal [41]	Material selection for AM technologies	Simple Additive Weighting; MOORA; TOPSIS; VIKOR
Poehler et al. [42]	Examine the priorities of patients and providers regarding amputation-level selection	Sheffield elicitation framework; Analytical Hierarchy Process (AHP)
Abas et al. [32]	Determination of AM materials for solid ankle foot orthoses	Simple Weighted Sum Product Method, MARCOS and TOPSIS
Jiryaei et al. [43]	Physical Therapy and Orthosis on Clinical Outcomes in Patients with Medial Knee OA	Visual analog scale and Western Ontario and McMaster Universities Osteoarthritis Index questionnaire.
Tiwari et al. [44]	Investigating the Efficacy of Indigenously produced Knee-Ankle-Foot Orthosis with Stance Control Knee Joint and Knee-Ankle-Foot Orthosis	Physiological Cost Index, and the Orthotics Prosthetics Users Survey-Health Quality of Life Index questionnaire
Estillore et al. [45]	Material identification research of prosthetic socket and pylon tube in transtibial prosthesis production	TOPSIS and PROMETHEE methods
Basat et al. [46]	Optimal material choice and design of external fixator clamp for metacarpal fractures	TOPSIS
Hafezalkotob and Hafezalkotob [47]	MULTIMOORA method with target-based traits and unified significant coefficients for materials selection in biomedical applications	Target-based MULTIMOORA method
Fu et al. [48]	Decision Support System for Ankle Foot Orthosis	Decision support system
Chia et al. [49]	Determination of Musculoskeletal Impairments and Propose Recommendations Using Gait Analysis in Children with Cerebral Palsy	Decision support system
Smirnova and Yuldashev [50]	Decision Making Support for Assessment of Functional Efficiency of Lower Limb Orthotics	Decision support system
Nayak et al. [51]	Utilization of Artificial Intelligence in Prosthetic and Orthotic Rehabilitation	Artificial Intelligence
Bawono et al. [52]	Ideal Process Parameters in CNC Milling of Insole Shoe Orthotic	Fuzzy Approach
Ahmed et al. [53]	FAHP/VIKOR Approach for Orthotic Medical Devices in Low-Income Countries	Fuzzy AHP/VIKOR Approach
Kirişci et al. [54]	Multi-criteria group decision-making and most ideal biomedical material selection	Fermatean fuzzy ELECTRE
Sofuoğlu [55]	New biomaterial selection approach	Novel MCDM method known as Reference Ideal Method
Exconde et al. [56]	Materials Selection of 3D Printing Filament	ELECTRE
Zhang et al. [57]	A case study related to biological nano-materials selection	TOPSIS
Kazemian et al. [58]	Intraoral stents for head and neck cancer patients undergoing radiation therapy	TOPSIS
Sanghvi et al. [59]	Material choice for bone staple (an Orthopaedic implant)	GRA and Fuzzy Logic
Grachev et al. [60]	Dental Material Selection for the AM	VIKOR method
Kumar et al. [61]	Selection of Materials for Knee Implant Femoral Component	Hybrid MCDM tactic
Ansaripour et al. [62]	Ranking biomaterials for spinal disc implants	Fuzzy AHP and TOPSIS decision making method
Pamucar et al. [63]	Biomaterial selection	Decision-making model integrating AHP as well as combinative distance-based assessment technique
Petković et al. [64]	Knee Prosthesis Biomaterial Selection by Using MCDM Solver	MCDM Solver

qualities of ABS include outstanding impact resistance and efficient processability [22]. TPU has exceptional mechanical qualities, namely superior tensile strength, tearing strength, and abrasion resistance in comparison with analogous thermoplastic elastomers [23]. PETG has garnered significant interest in recent times owing to its improved properties. It is widely recognized for its notable ductility and mechanical strength [24]. Polyamide (PA) has also garnered considerable attention due to its distinctive properties, rendering it an optimal selection for orthosis that necessitates both durability and flexibility. Therefore, considering the unique attributes displayed by different materials, a careful selection of five materials is conducted in this study, taking into consideration their availability and specific characteristics. These five materials are ABS, PLA, TPU, PETG, and Polypropylene (PP). Numerous researchers have employed these materials in the FDM process to fabricate knee orthoses [25–27].

MCDM approaches possess the capacity to construct decision rules by considering the relative significance of the factors under consideration, which ultimately determines the overall ranking of the alternatives [28–30]. Several researchers have previously employed MCDM techniques in the selection of optimal material for 3D printing [31,32]. Several methodologies have been devised for the material selection, notably TOPSIS [33], the Weighted Aggregated Sum Model [34], the Preference Ranking Organization Method for Enrichment Evaluation [35], and VIKOR [36]. Mohammed Abas et al. [32] in a study applied the MCDM technique based on eleven selection criteria and concluded that PLA was the ideal material for solid ankle foot orthoses. Taahirah Mangera et al. [37] used the ELECTRE III to help with the material selection process for a pediatric prosthetic knee, with light metals being considered as potential options for decision-making. Jayakrishna and Vinodh [38] introduced a comprehensive methodology that utilized the Grey Relational Analysis (GRA) technique to assess and prioritize materials according to their cost, material attributes, and environmental impact. In their study, Bhaskar and Khan [39] demonstrated the efficacy of five distinct hybrid MCDM approaches in the identification of the most optimum polymer-based biomaterial for application in the field of dentistry. Table 1 provides a review of MCDM techniques and their use in material selection for biomedical applications.

The literature has demonstrated that choosing a material is a difficult decision because there are many factors to consider. It has been described as a multifaceted, challenging problem. Appropriate criteria must be determined, together with their respective values, in order to assess various possibilities and make an accurate material selection decision. The selection of materials is more accurate when there are a greater number of criteria and their values are more exact, but problem-solving becomes a greater challenge. It is also underlined that in order to validate the outcomes, decision-making requires the application of several approaches. The research has also underscored that there are advantages and disadvantages to the objective and subjective weights that are used to determine the relevance of the criteria. Although the literature has addressed several material selection problems and the use of MCDM techniques, there is still plenty of room for improvement. An issue that has been noted in the literature is that rather than getting accurate values for the criteria, the researchers are relying more on literature, online resources, and supplier data. The principal causes are the cost of doing the experiments and the lack of resources. In order to close the gap in the literature, this work has focused on applying criteria values that are acquired through carefully planned experiments. Additionally, a material selection strategy based on several C-MCDM approaches has been established to choose the right material for orthoses. The established methodology is not just applicable to this specific application (material selection for orthotic applications); it can also be used in other medical or manufacturing applications where reliable material selection is needed.

3. Multi-Criteria Decision-Making Algorithms

In this work, the suitable polymer material for the orthosis application is chosen using C-MCDM methods. This system is distinct in that it maintains objectivity while eliminating bias in the material selection process by consolidating subjective and objective weights. The weights are combined using two approaches and the two methods are deployed to determine their impact or effectiveness on the result. The weights are integrated via a Bayes technique as reported in Refs. [65,66] as well as using a conventional method based on

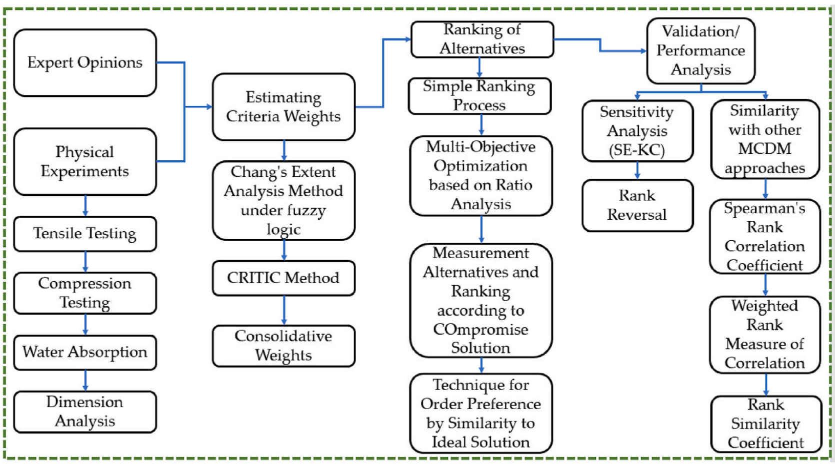

Fig. 2. Assessment of consolidative multi-criteria decision-making algorithms.

adding the two weights [67]. Fig. 2 outlines the complete system used in this research.

The first step in the methodology is to identify the polymer materials that have been documented in the literature as being most frequently used for orthotic applications and other medical devices. The next step is to decide which criteria need to be considered when comparing the various materials. Knowing which criteria have the most and least influence, as well as their relative importance, is equally crucial. The data collection is discussed in depth in the following section. After data collection, two procedures are adopted to estimate weights for the criteria: the subjective approach (CEA-FL) and the objective technique (in this case, CRITIC). The weights are then combined using the Bayes approach and the standard approach to figure out the final weights of criteria for ranking the alternatives.

The SRP, MOORA, MARCOS, and TOPSIS are four ranking techniques that are implemented, evaluated, and compared. Rank reversal analysis and SE-KC are used to evaluate the effectiveness of various MCDM strategies. The methodology also involves the utilization of different correlation coefficients to determine the similarity between various MCDM techniques. An overview of the several MCDM methods is provided below.

3.1. *Weight estimation*

The methodology utilized to ascertain the relative weights of the several criteria is depicted in Fig. 3. The first step is to estimate the subjective weights using CEA-FL and compute the objective weights using the CRITIC technique. After that, the subjective and objective weights are combined to get the final weights that are used to rank the different material options.

3.1.1. *Chang's Extent Analysis Method under fuzzy logic – subjective weights*

The fuzzy set axiom conceived by Zadeh [68] is adopted to address the imprecision and fuzziness of subjective viewpoints. The CEA-FL exhaustively and adequately handles distorted, mixed-up, and confused information as it is constituted on the cores of fuzzy set theory and hierarchical structural analysis. The CEA-FL is nothing but an extension of a customary Analytical Hierarchy Process (AHP) technique by means of fuzzy numbers (FNs) [69]. The elementary adaptation of the traditional AHP into Fuzzy-based AHP using CEA-FL was theorized by Van Laarhoven and Pedrycz [70], Buckley [71], and Chang [72]. They exploited triangular membership functions (MFs) to customize the crisp numbers of the Saaty scale into corresponding FNs. In this research, the crisp values are adapted into FNs via trapezoidal MF owing to their superior performance over the triangular MF [73]. The phases exercised to approximate fuzzy weights are described below.

3.1.1.1. Phase 1: Obtaining FNs. The decision matrices procured from multifarious experts are modulated into trapezoidal fuzzy numbers (TRFNs) in this phase. The MF of the F-designated TRFN with the properties (l, m, n, u) can be characterized via Eq. (1) [74].

$$\mathrm{MF}, \mu_F(x) = \begin{cases} 0 & x \le l \\ \dfrac{x-l}{m-l} & l \le x \le m \\ 1 & m \le x \le n \\ \dfrac{u-x}{u-n} & n \le x \le u \\ 0 & x \ge u \end{cases} \tag{1}$$

The Saaty scale-based significance values are primitively remodeled as triangular fuzzy numbers (TFNs) and thereafter as TRFNs to effectuate this metamorphosis. It is done by coherently preserving the upper and bottom extremities of the TFNs and marginally amending the center [75]. As a demonstration, the value of x (from the conventional Saaty scale) is first converted into TFN (a, b, c) where $a = x-1$; $b = x$ and $c = x+1$. Upon this rearrangement, the TFNs are modulated into TRFNs (l, m, n, u), where $l = a$; $u = c$; $m = l+0.5$ and $n = u-0.5$.

3.1.1.2. Phase 2: Weight processing. CEA-FL is preferred in this study to elicit the weights of the scientific requirements [72]. The CEA-FL for ciphering priori weights is summarized below [76,77].

Let $X = \{x_1, x_2, x_3, \ldots, x_n\}$ imply the grouping of objects and $G = \{g_1, g_2, g_3, \ldots, g_n\}$ indicate the collection of objectives. Every object must go through an extent analysis (EA) for each objective, in accordance with the CEA-FL framework. Thereupon, m EA values

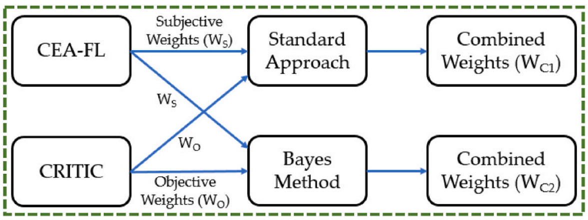

Fig. 3. Procedure for estimation of combined weights.

for each object are derived as $M_{gi}^1, M_{gi}^2, M_{gi}^3, M_{gi}^4, \ldots \ldots, M_{gi}^m$, i = 1, 2, 3, 4, …., n. Here, M_{gi}^j (j = 1, 2, 3, 4, …m) is the depiction of a TRFN. The ensuing steps can be pursued to conclude CEA-FL.

The synthetic fuzzy values for an ith object are deduced via Eq. (2).

$$S_i = \sum_{j=1}^{m} M_{gi}^j \otimes \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^j\right]^{-1} \tag{2}$$

As CEA-FL computes the weights using a TRFN with four values, the fuzzy addition is done using Eq. (3) to estimate $\sum_{j=1}^{m} M_{gi}^j$.

$$\sum_{j=1}^{m} M_{gi}^j = \left(\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} n_j, \sum_{j=1}^{m} u_j\right) \tag{3}$$

The value of $\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^j\right]^{-1}$ can be computed through the fuzzy addition of M_{gi}^j (j = 1, 2, 3, 4, …, m) values by applying Eq. (4).

$$\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^j = \left(\sum_{i=1}^{n} l_i, \sum_{i=1}^{n} m_i, \sum_{i=1}^{n} n_i, \sum_{i=1}^{n} u_i\right) \tag{4}$$

Further, the vector's inverse is specified via Eq. (5).

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^j\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} n_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i}\right) \tag{5}$$

Suppose $M_1 = (l_1, m_1, n_1, u_1)$ and $M_2 = (l_2, m_2, n_2, u_2)$ depicts two TRFNs. The condition in Eq. (6) entails how plausible it is that $M_2 = (l_2, m_2, n_2, u_2) \geq M_1 = (l_1, m_1, n_1, u_1)$.

$$V\ (M2 \geq M1) = \sup_{y \geq x} \left[min\left(\mu_{M_1}(x), \mu_{M_2}(y)\right)\right] \tag{6}$$

where $V\ (M_2 \geq M_1)$ can be demonstrated utilizing the definition in Eq. (7).

$$V\ (M2 \geq M1) = \text{hgt}\ (M1 \cap M2) = \mu_{M_2}(d) = \begin{cases} 1, & m_1 \geq m_2 \\ 0, & (m_2 - n_1) > (u_1 + l_2) \\ \dfrac{((n_1 - m_2) + (u_1 + l_2))}{(u_1 + l_2)}, & 0 < (m_2 - n_1) < (u_1 + l_2) \\ \dfrac{((m_2 - n_1) + (u_1 + l_2))}{(u_1 + l_2)}, & (m_2 - n_1) < (u_1 + l_2), where\ m_2 < n_1\ and\ m_1 < m_2 \end{cases} \tag{7}$$

A FN with a probability higher than k can be delineated as $V\ (M_2 \geq M_1, M_2, M_3, M_4, \ldots \ldots, M_k) = V\ [(M \geq M_1)$ and $V\ [(M \geq M_2)$ and $V\ [(M \geq M_3)$ and $V\ [(M \geq M_4)$ and …. and $V\ [(M \geq M_k)] = \min V\ (M \geq M_i)$, i = 1, 2, 3, …,k.

Considering that $d\ (A_i) = \min V\ (S_i \geq S_k)$ for k = 1, 2, 3, 4, …, n; $k \neq i$. The weight vector is acquired as presented in Eq. (8).

$$w' = (d'(A_1), d'(A_2), d'(A_3), d'(A_4), \ldots, d'(A_n))^T \tag{8}$$

where A_i (i = 1, 2, 3,4, …, n) imply n elements. The normalization is undertaken to determine the normalized weight vector (w) for the discrete elements as in Eq. (9).

$$w = (d(A_1), d(A_2), d(A_3), d(A_4), \ldots, d(A_n))^T = W_S \tag{9}$$

where w is a vector of non-FNs or crisp values and Ws represents subjective weights.

3.1.2. Criteria Importance Through Intercriteria Correlation – objective weights

The CRITIC is the method employed to estimate the objective weights in this paper. It is an empirical method that derives the weights based on the attribute's intrinsic information. As a consequence, uncertainty in the resulting weights can be minimized, producing results that are objective [78]. It leads to a larger weight for a criterion that exhibits greater degrees of conflict and variance with other criteria [79,80]. It is predicated on the quantitative analysis of the decision matrix to derive all relevant data from the assessment criteria. By using the inherent knowledge of the criteria, the CRITIC weight approach produces weights that are more accurate than biased [81]. When there are *m* options and *n* criteria, x_{ij} indicates the value for *j*th criterion and *i*th option. The objective weights using CRITIC can be calculated as described below [78].

The first step is to avoid the impact of various dimensions on the outcomes. Therefore, it is imperative to carry out the normalization process on each element. Consequently, Eq. (10) is used to accomplish normalization.

$$\begin{aligned} &For\ Profit\ Criteria, x_{ij}^{*} = \frac{x_{ij} - min\{x_{ij}\}}{max\{x_{ij}\} - min\{x_{ij}\}} \\ &For\ Loss\ Criteria, x_{ij}^{*} = \frac{max\{x_{ij}\} - x_{ij}}{max\{x_{ij}\} - min\{x_{ij}\}} \\ &(i = 1, 2, 3, 4, ..., m;\ j = 1, 2, 3, ..., n) \end{aligned} \tag{10}$$

The following step is to estimate the degree of conflict using Eq. (11). It assesses how a particular criterion conflicts with the decision-making scenario that is established by the remaining criteria.

$$R_j = \sum_{\substack{k=1 \\ k \neq j}}^{n} (1 - r_{jk}) \tag{11}$$

where r_{jk} is the Pearson correlation coefficient and is computed using Eq. (12).

$$r_{jk} = \left(\frac{\sum_{i=1}^{m} (x_{ij} - \overline{x_j})(x_{ik} - \overline{x_k})}{\sqrt{\sum_{i=1}^{m} (x_{ij} - \overline{x_j})^2} * \sqrt{\sum_{i=1}^{m} (x_{ik} - \overline{x_k})^2}} \right); \overline{x_j} = \frac{1}{m} \sum_{i=1}^{m} x_{ij}\ \&\ \overline{x_k} = \frac{1}{m} \sum_{i=1}^{m} x_{ik} \\ (j, k = 1, 2, 3, 4, ..., n;\ j \neq k) \tag{12}$$

Eq. (13) is utilized to approximate the value of information (C_j) included in the jth criterion.

$$C_j = S_j * R_j \tag{13}$$

where, S_j is the standard deviation, which is determined by applying Eq. (14) and indicates the degree of dispersion.

$$S_j = \sqrt{\frac{\sum_{i=1}^{m} (x_{ij} - \overline{x}_j)^2}{m-1}} \text{ and } \overline{x}_j = \frac{1}{m} \sum_{i=1}^{m} x_{ij} \tag{14}$$

The objective weights of the criteria are then obtained using Eq. (15).

$$W_o = \frac{C_j}{\sum_{j=1}^{n} C_j} \tag{15}$$

3.1.3. Consolidated weights

The subjective and objective weights are integrated using the two approaches. First, the method described in Ref. [67] is employed. This method, which uses Eq. (16), for combining the two weights together, is referred to in this work as the standard method.

$$W_{jC1} = \lambda W_{jS} + (1-\lambda) W_{jO} \tag{16}$$

where λ stands for the importance assigned to the type of weighting method. In this work, λ is assigned a value of 0.5. W_{jC1} indicates the combined weight for the jth criterion using the standard approach; W_{jS} refers to the weight of the jth criterion computed using the subjective approach; W_{jO} denotes the weight of the jth criterion computed using the objective approach.

In this work, the second method for combining the two weights is based on the Bayes equation, as stated in Refs. [65,66]. It is predicated on the idea of combining the weights using the geometric mean. This method makes use of Eq. (17), to estimate the combined weights.

$$W_{jC2} = \frac{W_{js} * W_{jo}}{\sum_{j=1}^{n} W_{js} * W_{jo}} \tag{17}$$

where W_{jC2} represents the combined weight for the jth criterion using the Bayes' approach.

3.2. Ranking methods

Analyzing the materials by determining the ranking orders of the various options comes next after the weight estimation. This paper uses four distinct approaches: SRP, MOORA, MARCOS, and TOPSIS. The subsequent subsections address these techniques.

3.2.1. Simple ranking process

This approach was developed by Ref. [14] to address MCDM challenges. It is one of the newest MCDM methods. This method avoids the complications of current MCDM methods and produces outcomes that are accurate and dependable, as demonstrated in Ref. [14]. Additionally, as it operates directly with criteria weights, no normalization procedure is necessary. SRP is one of the MCDM techniques used in this work because of its novelty and many advantages. The following procedures can be used to execute SRP.

Step 1. Establish the assessment criteria for the possibilities, where O_i signifies the alternatives and C_j represents the criteria, and i = {1, …, m} and j = {1, …, n}.

Step 2. Create the decision matrix (refer to Eq. (18)), denoted by D_{ij}, and d_{ij} describes the ith alternative's score relative to the jth criterion.

$$D = [d_{ij}]_{mxn} = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{m1} & d_{m2} & \ldots & d_{mn} \end{bmatrix} \tag{18}$$

Step 3. Define the ranks of the alternatives for each criterion, where the greater value of d_{ij} in the profit criteria ($\max_{1\le i\le m} d_{ij}$) and the lower value of d_{ij} in the non-beneficial criteria ($\min_{1\le i\le m} d_{ij}$) serve as the basis for the ranking procedure. The new ranking matrix is illustrated by the following equation, Eq. (19), where D'_{ij} is the ranking matrix and R_i^j is the rank of the ith alternative against the jth criterion.

$$D'_{ij} = R_i^j \tag{19}$$

Step 4. The weighted ranking matrix is formed in the fourth step using Eq. (20). W_j denotes the weights or relevance of the jth criterion, and D''_{ij} demonstrates the weighted ranking matrix.

$$D''_{ij} = W_j \, R_i^j \tag{20}$$

Step 5. Determine the alternatives' overall ranking score (RS_i) using Eq. (21).

$$RS_i = \sum_{j=1}^{n} W_j R_i^j \tag{21}$$

Step 6. Prioritizing alternatives based on the higher value of η (refer to Eq. (22), where m is the number of alternatives.

$$\eta = m - RS_i \tag{22}$$

3.2.2. Multi-objective optimization on the basis of ratio analysis

The MOORA approach was established by Brauers and Zavadskas [82]. The full multiplicative form, the ratio system, and the MOOSRA methods are the versions of the MOORA approach [83–87]. The steps for using various MOORA techniques are outlined below [82,83,87].

1) RATIO SYSTEM APPROACH

The decision matrix for the problem is established as the initial step in the MOORA approach. The decision matrix (Eq. (23)) demonstrates how several alternatives perform in relation to different criteria.

$$D = [d_{ij}]_{axb} = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{m1} & d_{m2} & \ldots & d_{mn} \end{bmatrix} \tag{23}$$

where, d_{ij} displays the evaluation value of the ith alternative on the jth criterion, where m and n are the corresponding counts of alternatives and criteria.

The second step is the normalization of decision matrix, D using Eq. (24). The resultant matrix is called as normalized decision matrix (NDM).

$$d_{ij}^* = \frac{d_{ij}}{\sqrt{\sum_{i=1}^{a} d_{ij}^2}} \quad i = 1, 2, 3, \ldots m \; j = 1, 2, 3, \ldots., n \tag{24}$$

d_{ij}^* is the dimensionless number that ranges from 0 to 1, it constitutes the normalized decision variable (NDV) of the ith alternative on the jth criterion.

The setup of a weighted decision matrix, W_{ij} using estimated weights as shown in Eq. (25) is the third step.

$$W_{ij} = w_j \text{ x } d^*_{ij} \tag{25}$$

where w_j is the weight of the jth criterion and it can be computed through different weighting methods. In this work, criterion weights are estimated using the CEA-FL technique.

The fourth step is the categorization of the favorable and the non-favorable criteria.

The impact score, β_i is computed in the fifth step using Eq. (26).

$$\beta_i = \theta^+_i - \theta^-_i \tag{26}$$

where θ^+ is the summation of favorable criteria as represented in Eq. (27) and θ^- is the summation of non-favorable criteria as represented in Eq. (28).

$$\theta^+_i = \sum_{j=1}^{g} W_{ij} \tag{27}$$

$$\theta^-_i = \sum_{j=g+1}^{b} W_{ij} \tag{28}$$

The choices are arranged in order of decreasing β_i values in the last step. The higher value of β_i indicates the higher rank.

2) FULL MULTIPLICATIVE FORM

Miller and Starr [88] introduced it for the first time. Its main advantages are that it is nonlinear, non-additive, and does not employ attribute weights [84]. This method uses Eq. (29) to calculate the overall utility, U_i of the ith option [89].

$$U_i = \frac{P_i}{Q_i} \quad i = 1, 2, 3, \ldots m \; j = 1, 2, 3, \ldots., n \tag{29}$$

where P_i is the multiplication of all criteria to be maximized and is estimated using Eq. (30)

Q_i is the multiplication of all criteria to be minimized and is estimated using Eq. (31)

$$P_i = \prod_{j=1}^{g} d_{ij} \tag{30}$$

$$Q_i = \prod_{j=g+1}^{b} d_{ij} \tag{31}$$

Finally, the alternatives are arranged in decreasing U_i values. The higher value of U_i denotes the higher rank.

3) MOOSRA APPROACH

It is a multi-objective optimization method that is less susceptible to significant variations in the values of the criteria [90]. The MOOSRA technique divides the total of the weighted NDVs for the positive criteria by the sum of the weighted NDVs for the negative criteria to determine the impact score (β_i) of each alternative (Eq. (32) [86].

The alternative with the greatest overall impact rating is chosen.

$$\beta_i = \frac{\theta^+_i}{\theta^-_i} \text{ For } \theta^+ \text{ and } \theta^-, \text{ see Eqs. (14) and} \tag{32}$$

3.2.3. Measurement of alternatives and ranking according to COmpromise solution

MARCOS is amongst the newest MCDM methods introduced by Stevic et al. [91]. This approach has been used in numerous studies, despite the fact that it was just developed relatively recently [92–94]. However, research utilizing the MARCOS approach to choose the material for orthoses has not yet been conducted. One of the primary justifications for choosing this MCDM approach is for this reason. The following are the steps needed for applying the MARCOS approach [91,95].

The first step is developing a decision matrix using Eq. (23) as shown in the above-mentioned MOORA. The formulation of an expanded initial decision matrix (see Eq. (33)) is the second step involving the inclusion of the ideal alternative (AI) and the anti-ideal alternative (AAI).

$$D_{exp} = \begin{bmatrix} d_{aa1} & d_{aa2} & \cdots & d_{aan} \\ d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{m1} & d_{m2} & \cdots & d_{mn} \\ d_{aI1} & d_{aI2} & \ldots & d_{aIn} \end{bmatrix} \tag{33}$$

where,

AAI = min (d_{ij}); i = 1, 2, 3, …, m j = 1, 2, 3, …, n if j is the higher the better.

AAI = max (d_{ij}); i = 1, 2, 3, …, m j = 1, 2, 3, …, n if j is the lower the better.

AI = max (d_{ij}); i = 1, 2, 3, …, m j = 1, 2, 3, …, n if j is the higher the better.

AI = min (d_{ij}); i = 1, 2, 3, …, m j = 1, 2, 3, …, n if j is the lower the better.

The expanded initial matrix is normalized in the third step using Eqs (34) and (35).

$$z_{ij} = \frac{d_{AI}}{d_{ij}} \text{ if j is the lower the better} \tag{34}$$

$$z_{ij} = \frac{d_{ij}}{d_{AI}} \text{ if j is the higher the better} \tag{35}$$

The weighted normalized expanded initial matrix is determined via Eq. (36) in the fourth step.

$$y_{ij} = w_j\, z_{ij} \tag{36}$$

where w_j is the weight of the j_{th} criterion.

The coefficients K_i^+ and K_i^- are obtained using Eqs (37) and (38) in the fifth step.

$$K_i^+ = \frac{S_I}{S_{AI}} \tag{37}$$

$$K_i^- = \frac{S_I}{S_{AAI}} \tag{38}$$

where, S_i, $S_{AAI,}$ and S_{AI} are the sum of the values of y_{ij}, d_{aai}, and d_{ai}, respectively, where i = 1, 2, …., a.

The sixth step involves computing the functions $f(K_i^+)$ and $f(K_i^-)$ using Eqs (39) and (40), respectively.

$$f\left(K_i^+\right) = \frac{K_i^-}{K_i^+ + K_i^-} \tag{39}$$

$$f\left(K_i^-\right) = \frac{K_i^+}{K_i^+ + K_i^-} \tag{40}$$

The function $f(K_i)$ is estimated using Eq. (41) in the final step and alternatives are ranked.

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1-f\left(K_i^+\right)}{f\left(K_i^+\right)} + \frac{1-f\left(K_i^-\right)}{f\left(K_i^-\right)}} \tag{41}$$

Lastly, choose the best solution according to the greater $f(K_i)$ value.

3.2.4. Technique for order of preference by similarity to ideal solution

As stated in Refs. [96,97], the TOPSIS selects a near-optimal solution. Its working is based on enlarging the distance from the negative ideal solution (NIS) and lessening the distance from the positive ideal solution (PIS). It is used in many fields, namely healthcare, warehouse management, inventory control, logistics department, supply chain planning, manufacturing processes, finance, etc.

Let J represent the set of benefit attributes or criteria (i.e., larger is better) and J' be the set of negative attributes or criteria (lesser is better). TOPSIS is implemented according to the following steps.

Step 1. Formation of an NDM utilizing Eq. (42). This translates various dimensions of the technical criteria into non-dimensional properties to enable their relationship.

$$r_{ij} = d_{ij} \Big/ \sqrt{\sum d_{ij}^2} \text{ for } i = 1, \ldots, m;\ j = 1, \ldots, n \tag{42}$$

Step 2. Creating the weighted NDM. Multiply each column of the standardized decision matrix by its weight. Now the new matrix element would become as in Eq. (43).

$$R_{ij} = w_j\ r_{ij} \tag{43}$$

Step 3. Computation of both positive and negative ideal solution sets utilizing Eq. (44).

$$\begin{aligned} &\text{PIS}, A+ = \{R1+, R2+, ..., Rm+\}; \\ &Rj+ = \{\ \text{maxi}\ (Rij)\ \text{if j}\ \ J\ ;\ \ \text{mini}\ (Rij)\ \text{if}\ \ j\ \ J'\ \} \\ &\text{NIS}, A- = \{R1-, R2-, ..., Rm-\}; \\ &Rj- = \{\ \text{mini}\ (Rij)\ \text{if j}\ \ J\ ;\ \ \text{maxi}\ (Rij)\ \text{if}\ \ j\ \ J'\ \} \end{aligned} \tag{44}$$

Step 4. Euclidean distances measurement from the PIS, A^+ (benefits) and NIS, A^- (cost) of each alternative through Eq. (45).

$$\begin{aligned} &Si+ = [\ \ (Rj + - Rij)2\ ]\ ½\ (i = 1, 2, ..., m;\ j = 1, 2, ..., n) \\ &Si- = [\ \ (Rj - - Rij)2\ ]\ ½\ (i = 1, 2, ..., m;\ j = 1, 2, ..., n) \end{aligned} \tag{45}$$

Step 5. Calculation of the relative closeness with reference to PIS for each alternative as stated in Eq. (46).

$$\theta_i = S_i^- \ / \ \left(S_i^+ + S_i^-\right), 0 \ < \ \theta_i \ < \ 1 \tag{46}$$

Step 6. Score the alternatives according to their relative adjacency. The option with the largest value of θ_i is optimal and must be chosen for the desired application.

3.3. Performance analysis - Validation

Assessing the degree to which the MCDM approach depends on the weights of the criteria is crucial when dealing with intricate MCDM problems that involve multiple alternatives and criteria. Measurement of a ranking's reliance on data contained in a criterion's associated data set is done through performance analysis. A greater dependence causes the approach to be more sensitive to changes in the weights of the criteria, which increases dependability [14]. SE-KC and rank reversal phenomenon are used in this work to assess the performance of the MCDM approaches.

3.3.1. Sensitivity analysis based on Kendall's coefficient of concordance

The reliability of the ranking effected through the above-mentioned MCDM techniques is gauged by means of sensitivity analysis. It is defined as a process for deciphering the effects of input parameter variances on a model's solutions [98]. It is unquestionably necessary to look into how variations in the input variables affect the output measures of the MCDM model [99,100]. If the result is sensitive to changes in input, the model is true and accurate. The common approach for sensitivity analysis is changing the weights of the attributes and observing how the results vary [101]. Preceding analyses have also demonstrated how significantly the ranks of the alternatives depend on the attribute weight coefficients [102]. As a result, sensitivity analysis based on changes in the weight coefficients is applied in this study to corroborate the effectiveness of the MCDM approach and confirm the veracity of the findings. The basic step in sensitivity analysis is the generation of new (arbitrary) weights for the criteria. It commences with the arbitrary selection of an attribute. The designated criterion's weight is then varied by a specific amount (rise or drop). Eventually, Eq. (47) is executed to enumerate the weights for the remaining criteria [103].

$$w_n^* = \frac{w_n\left(1 - w_i^*\right)}{(1 - w_i\ )} \tag{47}$$

where,

w_i: Initial weight for technical criteria i

w_i*: Weight elicited after updating the initial weight by a certain percentage

w_n: Initial *w*eight for technical criteria n

w_n*: Recomputed weight for criteria n.

To explore the analogy of ranks derived by changing the weights, Kendall's coefficient (Z) of concordance is employed [104,105]. Kendall's coefficient, whose values range from 0 to 1, manifests affinities in the resultant rankings. A value of 1 indicates complete agreement between the ranking orders derived from various MCDM approaches. Accordingly, if Z is nearer 1, the degree of resemblance will increase. Eqs. (48)–(50) are applied to compute the value of Z.

$$Z = \frac{12R}{m^2\ \left(k^3 - k\right)} \tag{48}$$

$$R_i = \sum_{j=1}^{m} r_{ij} \tag{49}$$

$$\mathrm{R} = \sum_{\mathrm{i}=1}^{\mathrm{k}} (\mathrm{R_i} - \overline{\mathrm{R}})^2 \tag{50}$$

where m is the count of schemes, k is the count of alternatives, and r_{ij} is the score that scenario i assigns to alternative j.

To derive the random weights for SE-KC, the following weight percentage-based scenarios are developed. These scenarios involve changing the weight of one criterion by a percentage and then using Eq. (47) to change the weights of the other criteria. The weights thus generated for each scenario are then combined through the Bayes approach. The generated random weights are then used in the SE-KC. Eventually, Z is calculated using Eqs. (48)–(50) to evaluate the reliability of the ranking results from different C-MCDM approaches.

- Scenario 1–40 % decrease in weight for tensile strength
- Scenario 2–10 % drop in weight for yield strength
- Scenario 3–20 % decrease in weight for compression strength
- Scenario 4–30 % reduction in weight for elongation at break
- Scenario 5–40 % rise in weight for yield strength ratio
- Scenario 6–20 % improvement in weight for water absorption
- Scenario 7–30 % increase in weight for shrinkage factor
- Scenario 8–20 % enhancement in weight for biocompatibility
- Scenario 9–30 % decrease in weight for affordability
- Scenario 10–40 % reduction in weight for printing simplicity

3.3.2. Rank reversal

The phenomenon of rank reversal is also investigated to aid in the analysis of the stability of different C-MCDM methods. It pertains to the incidence of alterations to the relative rankings of alternatives when a current alternative is eliminated from a set being assessed in a C-MCDM setting [106]. This behavior may result in inconsistent choices and complicate the process of contrasting and assessing options for various decision-making scenarios. This work employs two strategies—removing the least desired material and eliminating the low-weight criteria—to examine the rank reversal conundrum of C-MCDM methodologies.

3.4. Comparative ranking analysis

The comparative analysis evaluates the ranks that are obtained from various C-MCDM approaches using three similarity metrics, including SRC, WRC, and RSC [107–110]. This analysis is necessary to determine whether the two rankings are consistent or unreliable and to decide whether the order of the rankings is valid. Eq. (51) can be utilized to estimate the SRC (r_s).

$$r_s = 1 - \frac{6\sum d_i^2}{n\,(n^2 - 1)} \tag{51}$$

where d_i is the difference between the ranks from two different MCDM methods, n is the count of elements in the ranking.

The second correlation coefficient used in this investigation is known as the WRC (r_w). It can be expressed using Eq. (52).

$$r_w = 1 - \frac{6\sum_{i=1}^{n} d_i^2\,\left((n - R_{xi} + 1) + (n - R_{yi} + 1)\right)}{n^4 + n^3 - n^2 - n} \tag{52}$$

where R_{xi} and R_{yi} are the locations of the ith element in the ranking x and y.

The RSC (w_S), which is the third correlation coefficient employed in this study, is calculated using Eq. (53).

$$\mathrm{w_s} = 1 - \sum_{i=1}^{n} 2^{-R_{xi}}\,\frac{|R_{xi} - R_{yi}|}{\max\{|1 - R_{xi}|, |n - R_{xi}|\}} \tag{53}$$

4. Data collection

The choice of material for an orthosis is influenced by a number of technical factors. Mechanical, physical, and user-related attributes are some of these criteria. Tensile strength (C1), yield strength (C2), compression strength (C3), elongation at break (C4), and yield strength ratio (C5) are among the mechanical properties. Physical characteristics involve water absorption (C6) and shrinkage factor (C7). Other user-related qualities comprise biocompatibility (C8), affordability (C9), and printing simplicity (C10). The information regarding the material's mechanical and physical properties is gathered through the experiments as described in Fig. 4. The data about the affordability or cost is acquired from the filament supplier. The data on printing simplicity is determined based on the user experience by utilizing a Likert scale from 1 to 10, where 1 indicates the most challenging printing and 10 indicates the greater ease of printing. A material's biodegradability is indicated by a score between 0 and 1, where 0 denotes a material's non-biocompatibility and 1 denotes its biocompatibility. Water absorption, shrinkage factor, and cost are the three non-favorable or minimization criteria among the ten criteria, while the remaining seven are favorable or maximization criteria.

The various technical criteria can be explained as follows [111]. The ability of an orthosis to endure an externally imposed load without collapsing depends on its tensile strength. It suggests that the higher the tensile strength of the material, the more appropriate the material is. Likewise, the yield strength can be described as the highest stress a material can withstand before deforming irreversibly. It is particularly significant when it comes to knee orthoses or any other type of bespoke orthoses that favors greater yield strength materials. The reason for this is that knee orthoses and other customized orthoses are produced to fit each wearer's specific anatomy. The capacity of a material or structure to bear pressures that cause the material to contract in size is known as its compressive strength. Specific to this work, it can be stated as the highest load an orthosis can sustain before experiencing a 10 % relative distortion. "Elongation at Break" is a measure of the material's ductility. It is an estimate of the extent to which a material can be stretched as a percentage of its original dimension before breaking. This is also known as percentage elongation, and it quantifies the degree of plastic and elastic deformation a material can tolerate before fracturing. The final length of the material is contrasted with its initial length to calculate the percent elongation and the material's ductility. When paired with high yield strength, a material with a higher percent elongation is considered to be of superior quality. Another important variable that should be considered while designing an orthosis is the yield strength ratio. It describes the upper bound on the elastic stress that a specific material can tolerate. When it comes to resistance to permanent deformation under load, a material with a greater yield strength ratio performs better than one with a lower ratio. A material's tensile strength and yield strength are nearly equivalent when its yield strength ratio is higher. Therefore, a material intended for use in knee orthoses needs to have a higher yield strength ratio to give greater resilience. Water deteriorates the qualities of any polymer material that is applied to produce knee orthoses. The reason for this is that water gradually compromises the strength, stiffness, durability, and other properties of materials. Additionally, water creates an environment that is favorable to the growth of germs, which can lead to infections or skin irritations. Knee orthoses therefore require materials that are hydrophobic or have low water absorption. The ultimate effect of less water absorption is the increased durability of the material used to make knee orthoses. Furthermore, if the 3D-printed knee orthosis's measurements significantly deviate from the design specifications, the device won't fit the wearer correctly and will be uncomfortable. As a result, knowing how various polymers shrink and taking the necessary tolerance into consideration are essential when designing knee orthoses. A material with the lowest shrinkage factor needs to be considered for knee orthoses. Biocompatibility is the likelihood of an orthosis to interact with the human body safely, with little chance of causing itchiness, sensitivity, or allergic reactions while contacting the skin. The cost of the material also affects the affordability of an orthosis in addition to other expenses. The price of the orthosis will unavoidably decrease if the cost of a material decreases. Another crucial factor to consider when choosing an orthosis material is printing simplicity or ease. The reason for this is that while certain materials print readily, others have problems like poor adhesion, under-extrusion, weak layers, warping, delaminating layers, etc.

This work's goal is to employ more recent MCDM techniques in the selection of the best orthosis material. The data acquisition approach for different materials is discussed as follows. Tensile and compression tests are conducted in compliance with ASTM rules in order to gather data regarding tensile strength, yield strength, elongation at break, yield strength ratio, and compression strength. For this purpose, ASTM D638 (tensile specimens for PLA, ABS, and PETG), D412 (tensile specimens for TPU and PP), and D695 (compression specimens) standard specimens are 3D printed deploying the FDM process. Fig. 5 shows the Raise 3D pro 3 FDM 3D printer (Raise 3D Technologies Inc., Irvine, USA) that is utilized in this project. The 3D printing settings used for producing the standard specimens are compiled in Table 2. The 3D printing is undertaken when all required process parameters—such as the heated bed temperature, nozzle temperature, layer height, speed, and infill percentage—are established. The values for these variables are selected based on information provided by Raise 3D, the manufacturer of 3D printers [112–116]. This is due to the fact that the filaments utilized in this project are also acquired from Raise 3D, which had performed exhaustive experimentation to identify the ideal printing guidelines for every material. As seen in Fig. 6 (a)-(c), tensile and compression tests are carried out using a Zwick Z100 electromechanical universal testing equipment (ZwickRoell, Ulm, Germany) fitted with a 100 kN load cell.

In order to ascertain the water absorption capacity of each material, 3D printed samples are immersed in water at room temperature for intervals of 0.5, 2, 12, 24, 72, and 192 h [117,118]. Eq. (54) is applied to estimate the moisture intake of the printed samples, whereby W_i is the preliminary weight before water exposure and W_f is the final weight after moisture intake.

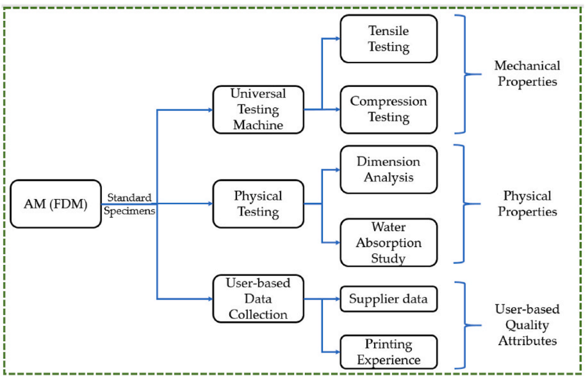

Fig. 4. Strategy adopted for data collection.

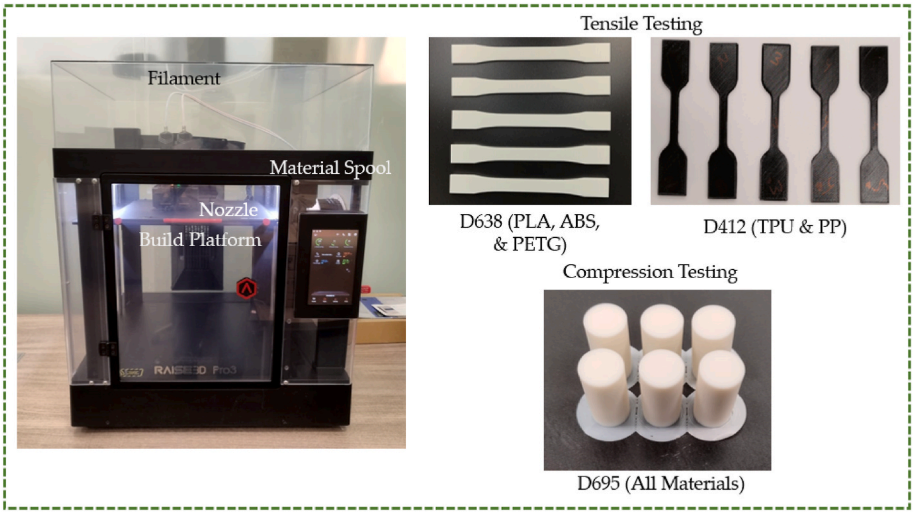

Fig. 5. FDM 3D Printer used in Experiments and fabricated standard specimens.

Table 2
3D Printing parameters utilized to fabricate the standard specimens.

Material	Parameters					
	Bed Temperature (°C)	Extrusion Temperature (°C)	Speed (mm/s)	Layer Height (mm)	Infill (%)	Extrusion Width (mm)
PLA	55	205	70	0.1	100	0.4
ABS	100	250				
PETG	60	245				
TPU	60	225	50			
PP	70	220	60			

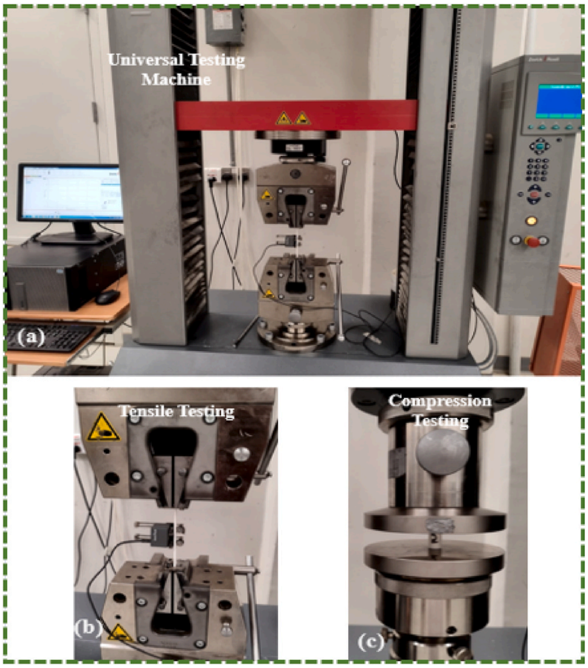

Fig. 6. (a) Universal testing machine; (b) Tensile testing set up; (c) Compression testing set up.

$$\text{Water absorption } (\%) = \frac{W_i\text{-}W_f}{W_i} \text{ x } 100 \tag{54}$$

Eq. (55) is implemented to calculate the shrinkage factor, where D_i is the original dimension (or design specification) and D_f is the dimension of the fabricated specimen. The 3D printed specimens are measured using the Coordinate Measuring Machine (CMM) as depicted in Fig. 7.

$$\text{Shrinkage factor } (\%) = \frac{D_i\text{-}D_f}{D_i} \text{ x } 100 \tag{55}$$

Table 3 provides the data that is collected through experimenting with various materials. The understanding of the relevance of technical criteria concerning material selection is equally as essential as the information gathered for the technical criteria. Certainly, in order to make the best decision, it is imperative to understand which specific characteristic should be prioritized more. This is achievable with the aid of professionals having experience in orthosis applications. So, five specialists from the academic, research, and medical fields are contacted to assess various technical parameters on a scale of 1–10, with 1 being the least significant and 10 being the most. The findings of their evaluation are displayed in Table 4.

5. Application

The material has an impact on the effectiveness and efficiency of an orthosis. The right approach must be used to choose the right material. The application of several MCDM techniques to determine the relevant material has therefore been demonstrated in this work. Establishing the importance or weight of criteria is the foremost step. The opinions of specialists and the values of the various selected technical criteria are the main inputs to the CEA-FL and CRITIC respectively.

In CEA-FL, after gathering the necessary data, the information provided by the experts is reviewed to determine whether or not their subjective assessment is accurate. As a result, the consistency ratio-based strategy developed by Prof. Saaty is embraced to gauge the experts' judgment [119]. A consistency ratio (CR) is produced by dividing the consistency index (CI) by the random consistency index (RI). In this process, the inconsistency is tolerable when the CR is 10 % or lower; if not, the judgment has to be revised. Past research reported in Ref. [120] presents the methodology for CR estimation. In the present work, the calculated CR is 0.81 %, 0.29 %, 0.75 %, 0.50 %, and 0.42 % for experts E1, E2, E3, E4, and E5, respectively, which is considerably below 10 %. This advocates that the opinions acquired in this work are satisfactory.

The fundamental step in the CEA-FL process is to tailor crisp values into FNs using Eq. (1), as illustrated in Table 5. The translated TRFNs (refer to Table 5) are then subjected to Eqs. (2)–(9) in order to derive the weights for technical criteria. The weights obtained are as follows: 0.1217, 0.1128, 0.1112, 0.0846, 0.1016, 0.0929, 0.1191, 0.1180, 0.0686, and 0.0693 for tensile strength, yield strength, compression strength, elongation at break, yield strength ratio, water absorption percentage, shrinkage rate, biocompatibility, affordability, and printing simplicity, respectively. Based on the weights result, it can be seen that experts propose that if the material is robust, resilient, and long-lasting, then the price is irrelevant. Therefore, the designer needs to choose a material with sufficient mechanical qualities rather than paying too much attention to affordability.

Eqs. (10)–(15) are applied to determine the objective weights using the CRITIC technique. The CRITIC-based objective weights for tensile strength, yield strength, compression strength, elongation at break, yield strength ratio, water absorption percentage, shrinkage factor, biocompatibility, affordability, and printing simplicity are 0.0789, 0.0700, 0.0755, 0.1887, 0.0761, 0.1421, 0.0694, 0.1395, 0.0768, and 0.0831 respectively. The combined weights obtained using Eqs. (16) and (17) are presented in Table 6.

After determining the significance of different attributes, the succeeding step is to apply the ranking approaches. In this work, SRP,

Fig. 7. CMM set up deployed to measure the 3D printed parts.

Table 3
Decision matrix comprising various orthosis materials and technical criteria [32].

Material	Criteria									
	C1 (MPa)	C2 (MPa)	C3 (MPa)	C4 (%)	C5	C6 (%)	C7 (%)	C8	C9 ($/Kg)	C10
ABS	24.58	20.36	50.03	3.86	82.82	1.44	1.18	0	25	9
PLA	30.84	25.94	51.93	3.56	84.11	1.37	0.46	1	25	9
PETG	29.23	18.98	44.94	3.62	64.92	1.59	0.85	0	40	9
TPU	28.07	6.15	6.73	340.90	21.92	1.29	1.19	0	35	6
PP	20.13	6.47	19.75	454.47	32.13	0.15	2.75	1	60	5

Table 4
Relevance or significance set by experts for different technical criteria.

Criteria	E1	E2	E3	E4	E5
Tensile Strength (C1)	9	10	10	10	9
Yield Strength (C2)	8	10	9	8	8
Compression Strength (C3)	8	10	8	8	8
Elongation at Break (C4)	7	10	7	7	7
Yield Strength Ratio (C5)	9	10	8	7	9
Water Absorption Percentage (C6)	9	10	6	9	8
Shrinkage Percentage (C7)	10	10	10	8	8
Biocompatibility (C8)	10	10	8	10	8
Affordability (C9)	10	5	8	7	6
Printing Simplicity (C10)	6	8	9	7	6

Table 5
Translation of crisp information into FNs.

Level of Significance	Description	TRFN	Level of Significance	TRFN
1	Same Impact	(1,1,1,1)		
3	Slightly Relevant	(2, 2.5, 3.5, 4)	0.3333	(0.25, 0.286, 0.4, 0.5)
5	High Influence	(4, 4.5, 5.5, 6)	0.2	(0.167, 0.182, 0.222, 0.25)
7	Very High Influence	(6, 6.5, 7.5, 8)	0.1429	(0.125, 0.133, 0.154, 0.167)
9	Extreme Impact	(9, 9, 9, 9)	0.1111	(0.111, 0.111, 0.111, 0.111)
2	Intermediate Levels	(1, 1.5, 2.5, 3)	0.5	(0.333, 0.4, 0.667, 1)
4		(3, 3.5, 4.5, 5)	0.25	(0.2, 0.222, 0.286, 0.333)
6		(5, 5.5, 6.5, 7)	0.1667	(0.143, 0.154, 0.182, 0.2)
8		(7, 7.5, 8.5, 9)	0.125	(0.111, 0.118, 0.133, 0.143)

variations of MOORA, as well as MACROS and TOPSIS are employed to rank the different materials. The primary step in the SRP is the computation of the decision matrix, d_{ij}, using Eq. (18).

$$d_{ij} = \begin{bmatrix} 24.58 & 20.36 & 50.03 & 3.86 & 82.82 & 1.44 & 1.18 & 0 & 25 & 9 \\ 30.84 & 25.94 & 51.93 & 3.56 & 84.11 & 1.37 & 0.46 & 1 & 25 & 9 \\ 29.23 & 18.98 & 44.94 & 3.62 & 64.92 & 1.59 & 0.85 & 0 & 40 & 9 \\ 28.07 & 6.15 & 6.73 & 340.90 & 21.92 & 1.29 & 1.19 & 0 & 35 & 6 \\ 20.13 & 6.47 & 19.75 & 454.47 & 32.13 & 0.15 & 2.75 & 1 & 60 & 5 \end{bmatrix}$$

The following step involves applying Eq. (19) to define the rank of the options for each criterion. This generates a new matrix called a ranking matrix, D'_{ij}.

$$D'_{ij} = \left[42232433111115131111233435234135525243345441415155 \right]$$

The fourth step involves utilizing Eq. (20) to create the weighted ranking matrix. The matrix constructed with the weights determined from the standard approach (W_{C1}) is displayed below. The computation results are displayed for the standard weight

Table 6
Consolidated weights estimated using standard and Bayes approaches.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
W_{C1}	0.1003	0.0914	0.0934	0.1366	0.0888	0.1175	0.0942	0.1287	0.0727	0.0762
W_{C2}	0.0974	0.0801	0.0853	0.1620	0.0784	0.1340	0.0838	0.1670	0.0535	0.0585

combination approach even in the other ranking methods.

$$D''_{ij} = \begin{bmatrix} 0.4012 & 0.1828 & 0.1868 & 0.4099 & 0.1777 & 0.4700 & 0.2827 & 0.3862 & 0.0727 & 0.0762 \\ 0.1003 & 0.0914 & 0.0934 & 0.6832 & 0.0888 & 0.3525 & 0.0942 & 0.1287 & 0.0727 & 0.0762 \\ 0.2006 & 0.2742 & 0.2802 & 0.5466 & 0.2665 & 0.5875 & 0.1884 & 0.3862 & 0.2909 & 0.0762 \\ 0.3009 & 0.4570 & 0.4669 & 0.2733 & 0.4442 & 0.2350 & 0.3769 & 0.3862 & 0.2182 & 0.3050 \\ 0.5016 & 0.3656 & 0.3736 & 0.1366 & 0.3553 & 0.1175 & 0.4711 & 0.1287 & 0.3637 & 0.3812 \end{bmatrix}$$

Eq. (21) is then used to estimate the total ranking score of the alternatives, and Eq. (22) is used to order the various alternatives according to the outcomes. The findings of the SRP are shown in Table 7.

PLA is the ideal material to utilize for knee orthoses since it has the highest overall score, as determined by the SRP (refer to Table 7).

The MOORA-based ratio system approach is the next strategy employed. The first step in this method as well, is to compute the decision matrix, d_{ij}, using Eq. (23). The second step entails creating the NDM, d_{ij}*, as shown below using Eq. (24). The third step is the generation of a weighted NDM, W_{ij}, using Eq. (25) as displayed hereunder.

$$d^*_{ij} = \begin{bmatrix} 0.4095 & 0.5210 & 0.5718 & 0.0068 & 0.5907 & 0.5039 & 0.3509 & 0.0000 & 0.2854 & 0.5162 \\ 0.5138 & 0.6637 & 0.5935 & 0.0063 & 0.5999 & 0.4794 & 0.1368 & 0.7071 & 0.2854 & 0.5162 \\ 0.4870 & 0.4857 & 0.5137 & 0.0064 & 0.4630 & 0.5564 & 0.2528 & 0.0000 & 0.4566 & 0.5162 \\ 0.4677 & 0.1574 & 0.0769 & 0.6000 & 0.1563 & 0.4514 & 0.3539 & 0.0000 & 0.3995 & 0.3441 \\ 0.3354 & 0.1656 & 0.2257 & 0.7999 & 0.2291 & 0.0525 & 0.8179 & 0.7071 & 0.6849 & 0.2868 \end{bmatrix}$$

$$W_{ij} = \begin{bmatrix} 0.0411 & 0.0476 & 0.0534 & 0.0009 & 0.0525 & 0.0592 & 0.0331 & 0.0000 & 0.0208 & 0.0394 \\ 0.0515 & 0.0607 & 0.0554 & 0.0009 & 0.0533 & 0.0563 & 0.0129 & 0.0910 & 0.0208 & 0.0394 \\ 0.0488 & 0.0444 & 0.0480 & 0.0009 & 0.0411 & 0.0654 & 0.0238 & 0.0000 & 0.0332 & 0.0394 \\ 0.0469 & 0.0144 & 0.0072 & 0.0820 & 0.0139 & 0.0530 & 0.0333 & 0.0000 & 0.0291 & 0.0262 \\ 0.0336 & 0.0151 & 0.0211 & 0.1093 & 0.0204 & 0.0062 & 0.0771 & 0.0910 & 0.0498 & 0.0219 \end{bmatrix}$$

The classification of beneficial and undesirable criteria is the fourth phase. Tensile strength, yield strength, compression strength, elongation at break, yield strength ratio, biocompatibility, and ease of printing are all beneficial criteria in this study. Water absorption percentage, shrinkage percentage, and cost are non-beneficial criteria. The impact score, β_i, is calculated in the final stage using Eqs. (26)–(28), as depicted in Table 8.

Thus, in accordance with the MOORA-ratio system approach, PLA has the greatest impact score, making it the best material to use for knee orthoses.

The third approach, referred to as the full multiplicative form, is based on the computation of overall utility using Eq. (29). The ratio between the product of the favorable criteria (derived using Eq. (30)) and the product of the unfavorable criteria (estimated using Eq. (31)) constitutes the overall utility. The result of the full multiplicative form approach has resulted in PP and PLA being the optimal material choice for knee orthoses.

PLA is the first-choice material for knee orthoses according to the MOOSRA technique, which is based on the computation of impact score using Eq. (32).

The MARCOS technique is another method used following the various MOORA-based C-MCDM approaches. This method commences by utilizing Eq. (23) to set up a decision matrix. The second step is to design an expanded initial decision matrix, D_{exp}, using Eq. (33).

$$D_{exp} = \begin{bmatrix} 24.58 & 20.36 & 50.03 & 3.86 & 82.82 & 1.44 & 1.18 & 0 & 25 & 9 \\ 30.84 & 25.94 & 51.93 & 3.56 & 84.11 & 1.37 & 0.46 & 1 & 25 & 9 \\ 29.23 & 18.98 & 44.94 & 3.62 & 64.92 & 1.59 & 0.85 & 0 & 40 & 9 \\ 28.07 & 6.15 & 6.73 & 340.90 & 21.92 & 1.29 & 1.19 & 0 & 35 & 6 \\ 20.13 & 6.47 & 19.75 & 454.47 & 32.13 & 0.15 & 2.75 & 1 & 60 & 5 \\ 30.84 & 90 & 51.93 & 454.47 & 84.11 & 0.15 & 0.46 & 1 & 25 & 9 \\ 20.13 & 2.4 & 6.73 & 3.56 & 21.92 & 1.59 & 2.75 & 0 & 60 & 5 \end{bmatrix}$$

The next step is the processing of the weighted normalized expanded initial matrix, y_{ij} (as shown below) using Eqs. (34)–(36). In the final step, the function $f(K_i)$ is estimated using Eqs. (37)–(41). The final rankings, which are presented in Table 9, confirm that PLA is the ideal material to use for knee orthoses.

Table 7
Ranking of alternatives using SRP.

Material	RS_i	η	Rank
ABS	2.6462	2.3538	2
PLA	1.7816	3.2184	1
PETG	3.0974	1.9026	3
TPU	3.4636	1.5364	5
PP	3.1949	1.8051	4

Table 8
Estimation of Impact score for different materials.

Material	θ_i^+	θ_i^-	β_i	Rank
ABS	0.2348	0.1130	0.1218	3
PLA	0.3522	0.0900	0.2622	1
PETG	0.2226	0.1224	0.1002	4
TPU	0.1906	0.1154	0.0751	5
PP	0.3124	0.1330	0.1794	2

$$y_{ij} = \begin{bmatrix} 0.0799 & 0.0717 & 0.0900 & 0.0012 & 0.0875 & 0.0122 & 0.0367 & 0.0000 & 0.0727 & 0.0762 \\ 0.1003 & 0.0914 & 0.0934 & 0.0011 & 0.0888 & 0.0129 & 0.0942 & 0.1287 & 0.0727 & 0.0762 \\ 0.0951 & 0.0669 & 0.0808 & 0.0011 & 0.0686 & 0.0111 & 0.0510 & 0.0000 & 0.0455 & 0.0762 \\ 0.0913 & 0.0217 & 0.0121 & 0.1025 & 0.0232 & 0.0137 & 0.0364 & 0.0000 & 0.0520 & 0.0508 \\ 0.0655 & 0.0228 & 0.0355 & 0.1366 & 0.0339 & 0.1175 & 0.0158 & 0.1287 & 0.0303 & 0.0424 \\ 0.1003 & 0.0914 & 0.0934 & 0.1366 & 0.0888 & 0.1175 & 0.0942 & 0.1287 & 0.0727 & 0.0762 \\ 0.0655 & 0.0217 & 0.0121 & 0.0011 & 0.0232 & 0.0111 & 0.0158 & 0.0000 & 0.0303 & 0.0424 \end{bmatrix}$$

The next C-MCDM method that is applied is the TOPSIS. The initial step is the establishment of a weighted NDM (R_{ij}) as stated below using Eqs. (23), (42) and (43). The quantification of Euclidean distances based on the PIS and NIS using Eqs. (44) and (45) is the next step in the TOPSIS technique. Lastly, the relative closeness with regard to the PIS (shown in Table 10) is estimated for each alternative via Eq. (46). Thus, PLA has been ranked second as an ideal material for knee orthosis based on the study done using TOPSIS.

$$R_{ij} = \begin{bmatrix} 0.0411 & 0.0476 & 0.0534 & 0.0009 & 0.0525 & 0.0592 & 0.0331 & 0.0000 & 0.0208 & 0.0394 \\ 0.0515 & 0.0607 & 0.0554 & 0.0009 & 0.0533 & 0.0563 & 0.0129 & 0.0910 & 0.0208 & 0.0394 \\ 0.0488 & 0.0444 & 0.0480 & 0.0009 & 0.0411 & 0.0654 & 0.0238 & 0.0000 & 0.0332 & 0.0394 \\ 0.0469 & 0.0144 & 0.0072 & 0.0820 & 0.0139 & 0.0530 & 0.0333 & 0.0000 & 0.0291 & 0.0262 \\ 0.0336 & 0.0151 & 0.0211 & 0.1093 & 0.0204 & 0.0062 & 0.0771 & 0.0910 & 0.0498 & 0.0219 \end{bmatrix}$$

Likewise, Table 11 compiles the rank of material alternatives estimated using the W_{c2} (weights from the Bayes approach) for various ranking techniques.

6. Results and discussion

This section focuses on explaining the results of various techniques and why PLA is the best material to utilize for orthotic applications. Additionally, it emphasizes on performance analysis of various C-MCDM techniques by presenting the findings for SE-KC and rank reversal phenomena. Furthermore, the outcome of the MCDM techniques using various correlation coefficients has been demonstrated.

6.1. Ideal material alternative for knee orthosis

Multiple distinct MCDM procedures are adopted in this investigation for the purpose of choosing the right material for knee orthosis. It is observed that the best material for knee orthosis, according to most of the approaches, is PLA. This is because it possesses the highest tensile, yield, and compression strengths as well as the lowest shrinkage (refer to Table 3). All experts have also emphasized the value of greater tensile, yield, and compression strengths and given these technical parameters the higher priority. The physiological objectives of knee orthoses encompass alleviating discomfort, deformity correction, limiting unnecessary joint mobility, enhancing joint motion, adjusting for anomalies, tissue protection, and fostering healing [121]. Therefore, the material chosen for the orthoses needs to be safe, durable, and strong enough to bear the highest stresses anticipated from being exposed to typical pressure by a combination of weight and gait, which produce tensile and compressive stresses. PLA is durable, biocompatible, and has the highest tensile and yield strengths of all the materials examined in this study. Its low shrinkage percentage, affordability, and ease of printing are the additional qualities that enable it to rank better as an orthosis material by various C-MCDM methodologies. ABS is the second-ranked material by the SRP. It can be attributed to its higher yield strength, considerable tensile strength, substantial compression resistance, low cost, and unchallenging printing. On the other hand, the other approaches rank it lower than PP. It might be a result of its lack of biocompatibility and lower demonstrated tensile strength compared to PLA. However, it can be used for

Table 9
Ordering of different materials using the MARCOS approach.

Material	K_i^+	K_i^-	$f(K_i^+)$	$f(K_i^-)$	$f(K_i)$	Rank
ABS	0.5282	2.3690	0.1823	0.8177	0.5076	3
PLA	0.7598	3.4075	0.1823	0.8177	0.7301	1
PETG	0.4962	2.2253	0.1823	0.8177	0.4768	4
TPU	0.4036	1.8100	0.1823	0.8177	0.3878	5
PP	0.6290	2.8210	0.1823	0.8177	0.6044	2

Table 10
Ranking of various materials using TOPSIS.

Material	S_i^+	S_i^-	$S_i^+ + S_i^-$	θ_i	Rank
ABS	0.1534	0.0889	0.2423	0.3670	4
PLA	0.1195	0.1413	0.2608	0.5419	2
PETG	0.1559	0.0834	0.2393	0.3485	5
TPU	0.1339	0.0963	0.2302	0.4183	3
PP	0.0996	0.1542	0.2539	0.6075	1

Table 11
Ranking of various materials based on W_{c2}.

Material	SRP	MOORA (Ratio System Approach)	MOOSRA	MARCOS	TOPSIS
ABS	2	3	3	3	4
PLA	1	1	1	1	2
PETG	3	5	5	4	5
TPU	5	4	4	5	3
PP	4	2	2	2	1

orthosis applications since it is an external device and if the ABS material is not causing any irritation to the skin of the patients.

PLA, which is ranked first, demonstrates that it makes a great choice for knee orthotic devices due to its superior characteristics. For instance, Sedigh et al. [122] employed PLA for orthopedic orthoses due to its extremely high flexural and shear strengths, as well as its environmental friendliness and biodegradability (because it is made from natural resources). Materials with high tensile strength, such as PLA, enhance the stabilization and adaptation of knee orthotic devices by minimizing pistoning or slipping during the gait cycle [121]. Furthermore, PLA has a low melting point (or has a low glass transition temperature ranging between 55 °C and 60 °C) that makes working with it simpler and requires not much energy to transition from a solid to a molten form [25,123]. Thus, due to its low melting point as well as minimal sensitivity to deformation and shrinkage, PLA makes printing easier [124]. Additionally, PLA has no known harmful effects when it comes into contact with skin and decomposes into a non-toxic acid at the end of its useful life [123]. However, ABS filaments are known to be more harmful to human health and have a higher risk of causing skin rashes and allergic responses [125]. Comparing PLA with TPU and PP, it can be seen that PLA tends to be stiffer and more rigid, making it a superior option for applications like knee orthoses where sturdiness and stability are essential [124]. It is widely recognized that knee orthoses are primarily made to bolster and stabilize the knee joint. TPU and PP necessitate more exact machine settings than PLA, making them more difficult to operate because of their flexibility and softness. Although TPU and PP are useful materials with a number of benefits, including low water absorption, elasticity, and resilience (see Table 3 for elongation at break, tensile strength, and water absorption), they are mostly used in applications where flexibility is crucial, such as shoe insoles. PLA ought to be the material of preference for knee orthoses, where stiffness and sturdiness are crucial. Additionally, using an Olympus BX53 M optical microscope (Olympus, Tokyo, Japan), a microscopic study of PLA and one of the lesser-performing materials, PETG, is undertaken to further ascertain and validate the rationale for PLA's higher performance. As Fig. 8(a) clearly illustrates, the farthest spacing separating two adjoining rasters is approximately 69 µm in the proximity of the PLA rupture location. Fig. 8(b) further shows that at proximity to the fracture site (in the case of PETG), the gap separating the two rasters is greater than 135 µm. Therefore, the higher mechanical properties of PLA can be linked to a reduced raster distance causing strong inter rasters.

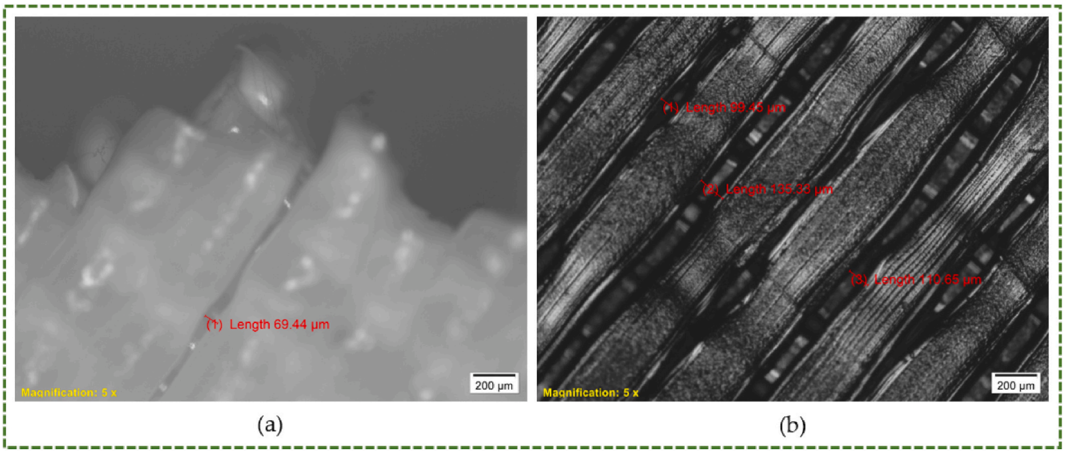

Fig. 8. Surface characterization of fabricated specimens (a) PLA; (b) PETG.

6.2. Performance analysis

The significance weights of the criteria are critical when assessing the alternatives in a problem involving decision-making. To demonstrate how sensitive the C-MCDM approaches are to the criteria weights, a comparison of the discrepancies in the produced outcomes is made using the various weights as indicated in Table 12. The process outlined in section 3.3.1 is used to determine the new weights.

Fig. 9(a)–(e) illustrates that there is a notable difference in the ranks of the alternatives when varying criteria weights are applied. Thus, this implies that the criteria weights have a significant influence on the performance of all C-MCDM approaches, with the exception of MOORA (full multiplicative form which is not dependent on criteria weights, refer to section 3.2.2). Thus, it demonstrates that the accuracy of criteria weights significantly affects the dependability of C-MCDM ranking algorithms.

Greater reliance on criteria weights indicates enhanced sensitivity of the MCDM technique to alterations in criteria weights, which increases the approach's reliability [14]. Eqs. (48)–(50) are used to figure out Z, which is used to measure the reliability of the different C-MCDM techniques. Reduced sensitivity to changes in the criteria weights and thus lower reliability are associated with higher values of Z, or vice versa. Fig. 10 illustrates the comparison of different C-MCDM methods based on their dependence on criteria weights. SRP appears to have the greatest dependence on the criteria weights due to its lowest Z value. Comparing the TOPSIS method to the other methods under consideration, it has the highest Z value and the least dependence on the criteria weights. The assertion suggests that SRP is the most dependable strategy when compared to the other C-MCDM methodologies under discussion.

The rank reversal phenomenon can result in inconsistent choices and make it difficult to assess and contrast options in a variety of decision-making scenarios. The first method used to study the occurrence of rank reversal in various C-MCDM methods involves removing the least preferred material alternative. The consequence of omitting the least performing material on the effectiveness of different C-MCDM techniques is shown in Fig. 11(a)–(f). It is acknowledged that the rank reversal issue has no bearing on any of the approaches under consideration. It is demonstrated that, in the event that the least preferred alternative is eliminated, none of the C-MCDM techniques taken into consideration result in rank reversal.

The second technique for examining the likelihood of rank reversal in different C-MCDM approaches is to eliminate the least important criterion. The criterion "affordability" has been eliminated from the list of criteria, since it receives the lowest weight. Fig. 12 (a)–(e) illustrate the impact of leaving out the least significant criterion on the efficacy of different C-MCDM techniques. It has been observed that the alternatives' ranks have changed in MOORA (Ratio System) and MOOSRA-based C-MCDM methods. For instance, the initial rankings of PETG and TPU are 5 and 4, respectively; however, when the least important criterion is eliminated, their rankings are inverted. Nevertheless, the elimination of the least important criterion has no effect on the ranks generated by SRP, MARCOS, or TOPSIS, suggesting that they are rank reversal-free.

6.3. Similarity between MCDM methods

Three correlation coefficients have been used in this section to measure the degree of rank similarity across various C-MCDM approaches. Fig. 13 (a)-(c) displays the results of the three correlation coefficients, which are SRC, WRC, and RSC, respectively, computed using Eqs. (51)–(53). These coefficients are estimated for the two weighing techniques (Wc1 and Wc2). Higher values of these coefficients, or values nearer 1, indicate a stronger correlation or similarity in ranks between the two approaches. Similarly, a value of 1 denotes an exact match between the ranks of the two methods. There is a significant discrepancy between the rankings of the two methods when the coefficients have a negative value. The RSC measure is unbalanced due to its reliance on the importance of the position in the ranking of the primary MCDM method. Additionally, it can be shown in Fig. 13(c), where the array has distinct transposition properties and is asymmetrical.

SRP has a good correlation with the MOORA, MOOSRA, and MARCOS approaches, but a very weak correlation with the TOPSIS approach, according to a comparison of methodologies. For instance, SRP-MARCOS (Fig. 13(a), Wc1) has a value of 0.70, meaning that the ranks of the two approaches are 70 % identical. Likewise, MOORA, MOOSRA, and MARCOS exhibit substantial correlations with one another and yield highly comparable ranks. However, their rankings differ considerably from that of the TOPSIS.

The blend of subjective and objective weights as well as the application of several MCDM methodologies employed in this work meets the criteria for reasonable, useful, and methodical procedures. They are useful in enabling to selection of the optimal material for knee orthoses. It is essential to determine the best strategy since there are numerous MCDM techniques presently in use, each having benefits and drawbacks. Different MCDM strategies may result in distinct outcomes. The efficacy of the decision and the amount of work that has to be done are greatly influenced by the choice of an appropriate MCDM approach. Several MCDM models can rank alternatives in different orders. The complexity levels and computational requirements of the various techniques also differ. In order to make the findings more applicable and reliable, it is therefore always advised to apply more than one MCDM technique.

Table 12
Combined weights estimated using standard and Bayes approaches.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
W_{C1}	0.1003	0.0914	0.0934	0.1366	0.0888	0.1175	0.0942	0.1287	0.0727	0.0762
W_{C2}	0.0974	0.0801	0.0853	0.1620	0.0784	0.1340	0.0838	0.1670	0.0535	0.0585
CEA-FL	0.1217	0.1128	0.1112	0.0846	0.1016	0.0929	0.1191	0.1180	0.0686	0.0693
New Weights	0.0150	0.0092	0.0100	0.3848	0.0113	0.1569	0.0188	0.3922	0.0007	0.0010

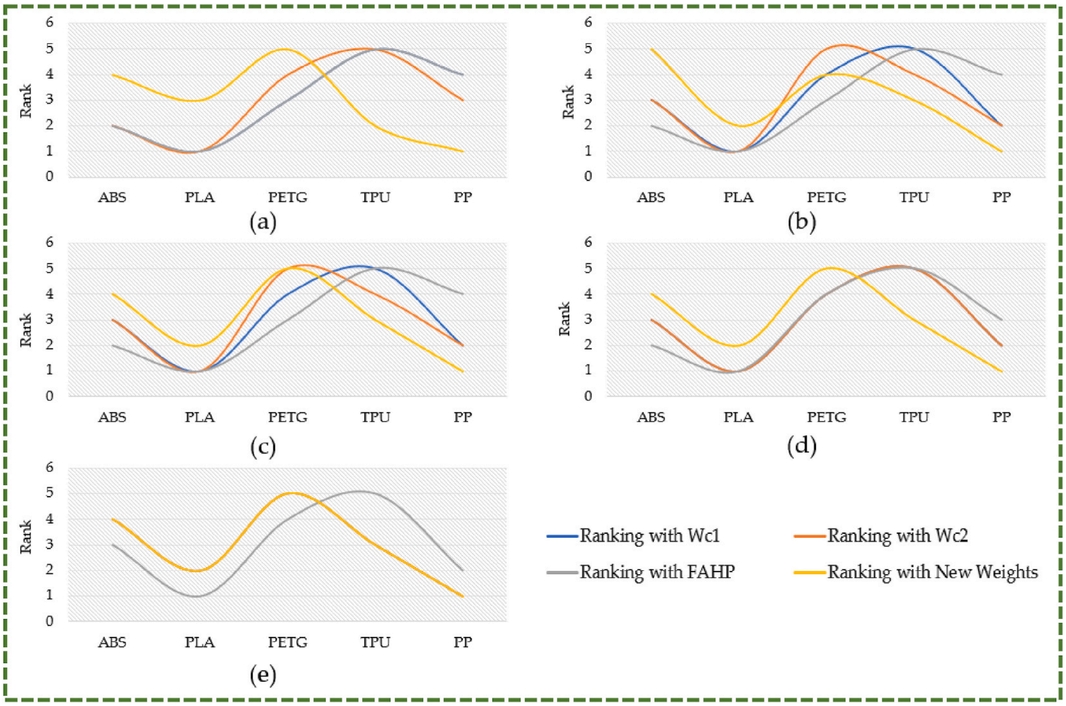

Fig. 9. Analysis of rankings influenced by the criteria weights for (a) SRP; (b) MOORA (Ratio System Approach; (c) MOOSRA; (d) MARCOS; (e) TOPSIS.

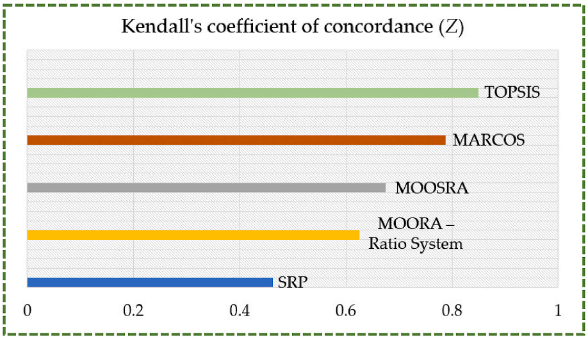

Fig. 10. Dependability of C-MCDM methods on criteria weights.

The study is unique in that it considers several aspects of identifying a material for an orthotic application. The deployment of many MCDM techniques in the present research strengthens the selection process' flexibility, accuracy, and usefulness. The implemented MCDM approaches are highly helpful for selecting materials for knee orthoses or other similar medical devices where the degree of indecisiveness is projected to change depending on user requirements and experts' opinions. However, these selection procedures may turn monotonous, computationally challenging, and tiresome as the number of criteria and potential materials rises. Furthermore, because the efficiency of the majority of these decision-making processes relies on expert judgments, they typically tend to overestimate the ranking process. Consequently, it is essential to use objective weights in addition to subjective weights to provide impartiality and realism to decision-making. This research aims to help users choose the best material because the fundamental issue of orthoses material selection using multiple MCDM approaches has not been handled with proactive rigor due to its unpredictable nature.

7. Conclusion

Now that AM has advanced, it is possible to actualize any complex geometry, including orthoses. Numerous advantages of AM include the ability to manufacture customized products, shorter manufacturing times, more flexible design options, less material waste, etc. However, because there are so many materials available for AM, it has become extremely challenging for customers to

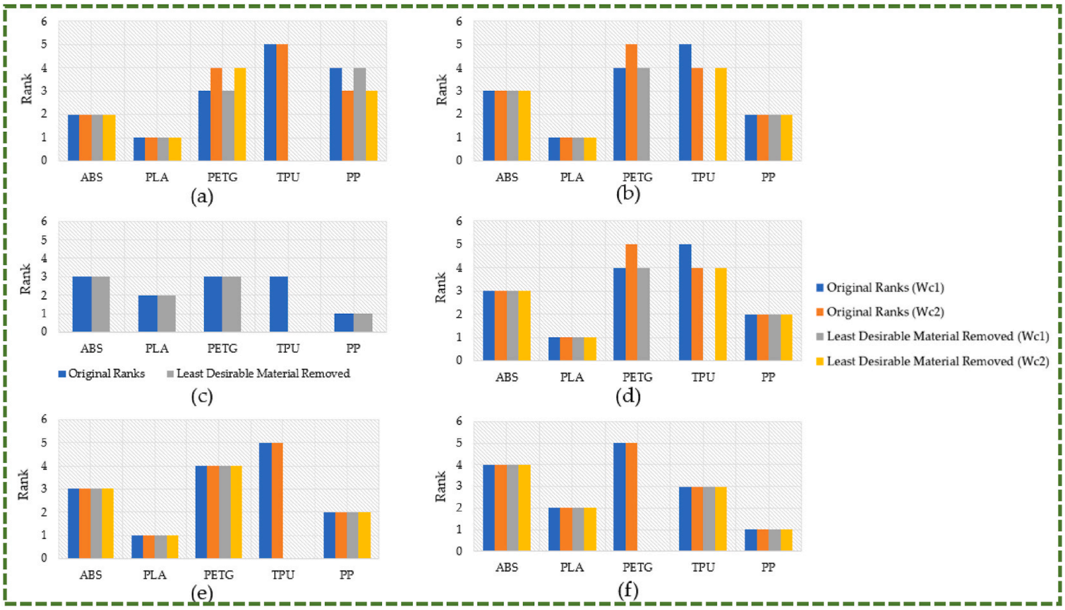

Fig. 11. Influence of least desired material removal on the ranks of (a) SRP; (b) MOORA-Ratio System; (c) MOORA – Full Multiplicative; (d) MOOSRA; (e) MARCOS; (f) TOPSIS.

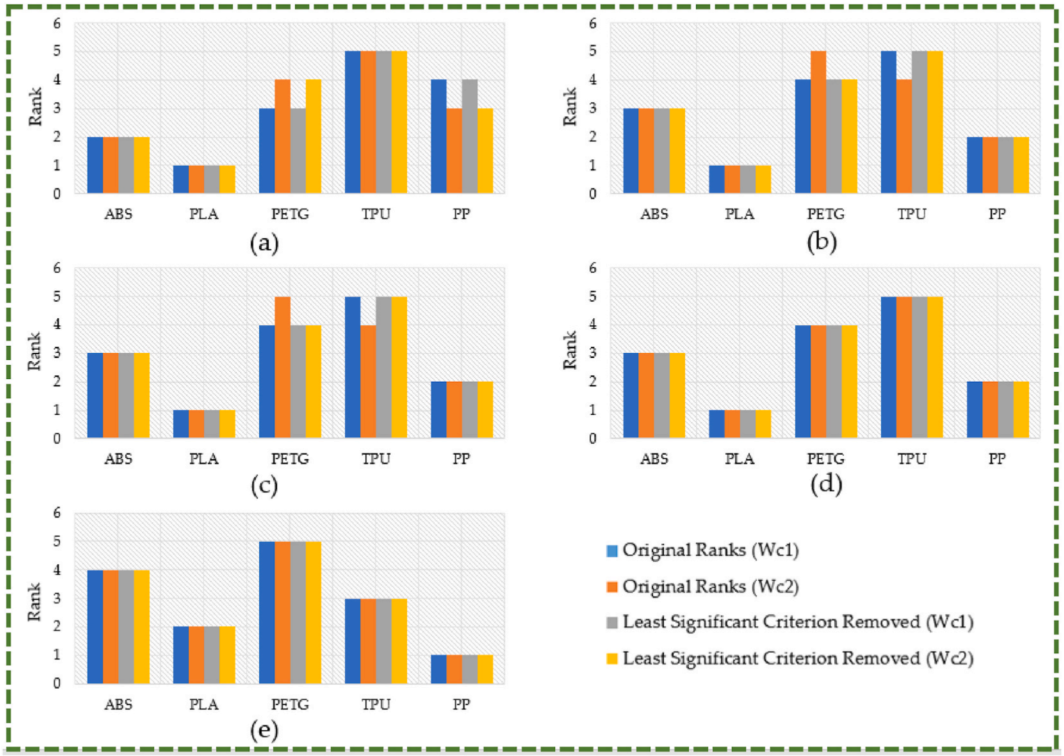

Fig. 12. Influence of least significant criterion removal on the ranks of (a) SRP; (b) MOORA-Ratio System; (c) MOOSRA; (d) MARCOS; (e) TOPSIS.

choose the right materials for their application. Therefore, the focus of this work is on choosing the right material for knee orthoses. Similar to AM materials, there are a variety of MCDM methodologies available, and users frequently struggle to decide which one is best for their application. This work has therefore used a variety of MCDM techniques to choose the proper material for knee orthoses. It is imperative to emphasize multiple criteria that serve as the foundation for evaluating various alternatives in the majority of MCDM

MCDM Methods (Wc1)	SRP	MOORA-Ratio System	MOOSRA	MARCOS	TOPSIS
SRP	1	0.70	0.70	0.70	-0.10
MOORA-Ratio System	0.70	1	1	1	0.60
MOOSRA	0.70	1	1	1	0.60
MARCOS	0.70	1	1	1	0.60
TOPSIS	-0.10	0.60	0.60	0.60	1

MCDM Methods (Wc2)	SRP	MOORA-Ratio System	MOOSRA	MARCOS	TOPSIS
SRP	1	0.80	0.80	0.90	0.30
MOORA-Ratio System	0.80	1	1	0.90	0.80
MOOSRA	0.80	1	1	0.90	0.80
MARCOS	0.90	0.90	0.90	1	0.60
TOPSIS	0.30	0.80	0.80	0.60	1

(a)

MCDM Methods (Wc1)	SRP	MOORA-Ratio System	MOOSRA	MARCOS	TOPSIS
SRP	1	0.70	0.70	0.70	-0.07
MOORA-Ratio System	0.70	1	1	1	0.65
MOOSRA	0.70	1	1	1	0.65
MARCOS	0.70	1	1	1	0.65
TOPSIS	-0.07	0.65	0.65	0.65	1

MCDM Methods (Wc2)	SRP	MOORA-Ratio System	MOOSRA	MARCOS	TOPSIS
SRP	1	0.83	0.83	0.88	0.30
MOORA-Ratio System	0.83	1	1	0.95	0.77
MOOSRA	0.83	1	1	0.95	0.77
MARCOS	0.88	0.95	0.95	1	0.65
TOPSIS	0.30	0.77	0.77	0.65	1

(b)

MCDM Methods (Wc1)	SRP	MOORA-Ratio System	MOOSRA	MARCOS	TOPSIS
SRP	1	0.81	0.81	0.81	0.51
MOORA-Ratio System	0.75	1	1	1	0.69
MOOSRA	0.75	1	1	1	0.69
MARCOS	0.75	1	1	1	0.69
TOPSIS	0.36	0.64	0.64	0.64	1

MCDM Methods (Wc2)	SRP	MOORA-Ratio System	MOOSRA	MARCOS	TOPSIS
SRP	1	0.83	0.83	0.85	0.55
MOORA-Ratio System	0.83	1	1	0.97	0.71
MOOSRA	0.83	1	1	0.97	0.71
MARCOS	0.85	0.97	0.97	1	0.69
TOPSIS	0.49	0.71	0.71	0.64	1

(c)

Fig. 13. Similarity Analysis using correlation coefficients (a) SRC; (b) WRC; (c) RSC.

approaches. There are plenty of processes that have been employed in the literature, but fuzzy-based approaches are more trustworthy since they consider the uncertainty and bias of expert judgment. It is also crucial to keep in mind that the experts' opinions may alter based on the application, which would alter the weights of the criteria and, ultimately, the result. Therefore, it is crucial to thoroughly describe the application where the MCDM will be employed.

This work explores two aspects: selecting appropriate material for knee orthoses and using cutting-edge MCDM methods. There are two objectives for this work. A methodology for MCDM based on consolidative weights is presented and examined in the first objective. The integration of the subjective and objective weights constitutes the methodology's cornerstone. Subjective weights are estimated using the CEA-FL, and objective weights are determined using the CRITIC method. Multiple ranking algorithms are utilized to assess various material alternatives, such as the SRP, MOORA, MARCOS, and TOPSIS. The second objective is the investigation of five alternative materials using ten well-chosen considerations that encapsulate the fundamental aspects needed for the AM of orthoses. It involves conducting in-depth experiments to ascertain the values of various criteria as well as obtaining expert opinions regarding the significance of these criteria.

The results of the investigation suggested that PLA is, by far, the most effective material for knee orthoses. Its superior tensile, yield, and compression strengths, along with its minimal shrinkage, low cost, and ease of printing account for this. Among the C-MCDM methods under assessment, SRP tends to be the most reliant on the criteria weights, suggesting that it is the most dependable approach. It is also established that SRP, MARCOS, and TOPSIS approaches are rank-reversal free. Although SRP has very little correlation with the TOPSIS technique, it has strong correlations with MOORA, MOOSRA, and MARCOS approaches.

One of the main criticisms of MCDM is that different approaches to the same problem may result in different solutions. The optimum outcome can therefore be one that is persistent in several MCDM methods. The various MCDM approaches may not produce the same results. Different weights and their dissimilar principles, in addition to different solution techniques, can account for this. It makes sense to use one of the most straightforward methods. However, it is recommended to utilize a range of approaches to attain conformity and enhance the reliability of the results.

The approach presented in this work is particularly helpful for material selection and other problems of a similar nature, where varying degrees of uncertainty are anticipated because of the competitive and volatile nature of the market together with changing user preferences. With more criteria and diverse material kinds, this method could become laborious, computationally intensive, and demanding. Additionally, the ranking procedure could seem exaggerated because the efficacy of the adopted approach depends on experts' evaluations. Therefore, a detailed investigation into the integrity of the fuzzy pairwise comparison matrix using TRFNs will be helpful in the future. Owing to the transient nature of the AM industry and evolving consumer opinions, the database must be refreshed on regular basis with new materials and criteria. Henceforth, more materials and criteria will be investigated in subsequent studies to build a more realistic material selection system. The authors additionally seek to apply different decision models—for example, a computational model based on extended linguistic hierarchies [126], a strategy based on imbalanced hesitant fuzzy linguistic sets [127], etc.—to address the stated material selection problem.

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Ethical statement

Not Applicable. Approval by an ethics committee or informed consent was not required for this study because it did not include any human or animal subjects.

Data availability statement

The article contains all of the data (as tables and figures as well as within the text) that has been utilized in this study.

CRediT authorship contribution statement

Syed Hammad Mian: Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Emad Abouel Nasr:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Khaja Moiduddin:** Writing – original draft, Methodology. **Mustafa Saleh:** Methodology, Data curation. **Mustufa Haider Abidi:** Writing – review & editing, Data curation. **Hisham Alkhalefah:** Resources, Project administration, Formal analysis.

Declaration of competing interest

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

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Abbreviations

OA	Osteoarthritis
3D	Three-dimensional
AM	Additive manufacturing
FDM	Fused Deposition Modelling
MCDM	Multi-Criteria Decision-Making
C-MCDM	Consolidative MCDM
CRITIC	CRiteria Importance Through Intercriteria Correlation
SRP	Simple Ranking Process
MOORA	Multi-Objective Optimization based on Ratio Analysis
MARCOS	Measurement alternatives and ranking according to compromise solution
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
SE-KC	Kendall’s Coefficient of Concordance
SRC	Spearman’s Rank Correlation Coefficient
WRC	Weighted Rank Measure of Correlation
RSC	Rank Similarity Coefficient
PLA	Polylactic Acid
ABS	Acrylonitrile Butadiene Styrene
PETG	Polyethylene Terephthalate Glycol
TPU	Thermoplastic Polyurethane
PP	Polypropylene
GRA	Grey Relational Analysis
AHP	Analytical Hierarchy Process
FNs	Fuzzy Numbers
MFs	Membership Functions
TRFNs	Trapezoidal Fuzzy Numbers
TFNs	Triangular Fuzzy Numbers
EA	Extent Analysis
NDM	Normalized Decision Matrix

NDV	Normalized Decision Variable
AI	Ideal Alternative
AAI	Anti-Ideal Alternative
NIS	Negative Ideal Solution
PIS	Positive Ideal Solution
CMM	Coordinate Measuring Machine
CR	Consistency Ratio
CI	Consistency Index
RI	Random Consistency Index

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