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APPLICATION OF FUZZY MCDM IN SELECTING ECO-FRIENDLY MATERIALS FOR ELECTRIC VEHICLE INTERIORS

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The growing demand for sustainable solutions in the automotive industry has led to a significant focus on eco-friendly materials for electric vehicle (EV) interiors. This research paper explores the application of Fuzzy Multi-Criteria Decision-Making (MCDM) in selecting optimal eco-friendly materials for EV interiors. Fuzzy MCDM provides a robust framework to handle the inherent uncertainty and subjectivity in evaluating multiple criteria such as recyclability, durability, strength, comfort, aesthetic appeal, carbon footprint, price, energy requirements, and complexity in manufacturing. By employing a combination of Fuzzy-Entropy and Fuzzy-TOPSIS, this study aims to prioritize materials that offer the best balance of environmental sustainability and performance. Entropy is employed to evaluate the criteria weights, whereas TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is applied to select the ideal sustainable materials for EV interiors and to rate the alternatives. The final result reveals that Polyethylene Terephthalate is the most suitable material alternative for EV interiors, significantly enhancing the sustainability of the automotive industry. In contrast, Bamboo Fiber Composite ranks the lowest among the alternatives, indicating it is the least favorable option in the group. The final outcomes from the fuzzy-entropy-TOPSIS model are also compared to six others solo MCDM models and the ranking stability is also verified through sensitivity analysis.

Keywords: electric vehicle, eco-friendly materials, Fuzzy MCDM, entropy, TOPSIS

HIGHLIGHTS

- Developed a hybrid Fuzzy-Entropy-TOPSIS model for sustainable EV interior material selection.
- PET identified as the top eco-friendly material, combining performance, cost, and sustainability.
- Model integrates objective entropy weights with fuzzy logic to manage decision uncertainty.
- Validated ranking robustness via sensitivity analysis and comparison with six MCDM models.

1 Introduction

The automotive industry heavily contributes to pollution due to fossil fuel reliance and non-renewable materials. With rising concerns over climate change and resource depletion, a shift to sustainable practices is essential. Electric vehicles (EVs) help reduce emissions and fossil fuel dependency, but sustainability also depends on interior materials [1]. Traditional materials like plastics, synthetic leathers, and metals have significant environmental impacts from extraction to disposal. Thus, the adoption of eco-friendly materials in EV interiors is increasingly prioritized.

Stricter environmental regulations worldwide are driving automakers to adopt eco-friendly materials and practices to curb pollution and promote sustainability. Growing consumer awareness of environmental impacts is also shifting preferences toward sustainable products, pushing the automotive industry to explore greener alternatives. Many companies are integrating eco-friendly materials into their vehicle interiors to align with corporate social responsibility goals and demonstrate commitment to sustainability. Advances in material science have made it possible to develop innovative, high-performance sustainable materials that do not compromise quality or functionality [2,3]. A lifecycle assessment approach further emphasizes the importance of minimizing environmental impact, as eco-friendly materials often require less energy, produce fewer emissions, and offer better recyclability. In a competitive market, automakers that prioritize sustainability can differentiate themselves, attract environmentally conscious consumers, and strengthen their brand image while contributing to a greener future.

Selecting materials for EV interiors is a strategic decision impacting both sustainability and brand positioning. Given the complexity of balancing environmental, economic, and performance criteria amid uncertainty, a systematic approach is essential. Key drivers include stringent regulations, shifting consumer preferences, corporate sustainability commitments, and material advancements [4]. Understanding lifecycle impacts and leveraging sustainability for market differentiation further highlight the need for this research. By employing Fuzzy MCDM, this study provides a robust framework for sustainable material selection. Fuzzy logic effectively handles uncertainty in decision-making, making it ideal for this task [2]. Specifically, Fuzzy Entropy determines criterion weights based on uncertainty, while Fuzzy TOPSIS ranks materials based on performance.

Selecting eco-friendly materials for EV interiors is complex due to conflicting criteria, including environmental impact, cost, performance, aesthetics, and regulations. Traditional methods struggle with these intricacies and uncertainties. Natural fibers may be sustainable but costly and less durable, while recycled materials aid conservation but pose quality and availability issues. Stakeholder priorities also vary—designers focus on aesthetics, engineers on performance, and procurement on cost. Additionally, data on environmental impact, recyclability, and lifecycle analysis is often incomplete, complicating assessments. To address these challenges, this research develops a Fuzzy MCDM framework, integrating fuzzy logic to manage uncertainty in decision-making [4,5]. This approach provides actionable insights for automotive stakeholders, supporting sustainable material selection and advancing environmental sustainability.

This study presents a novel and original contribution to the field of sustainable material selection for electric vehicle (EV) interiors by integrating Fuzzy-Entropy with Fuzzy-TOPSIS in a hybrid MCDM framework. Unlike previous works that primarily rely on subjective expert weighting or conventional MCDM models, this study uniquely combines objective entropy-based weighting with fuzzy logic to effectively manage both quantitative data and qualitative uncertainties. This dual-layered approach allows for a more accurate and balanced evaluation of eco-friendly materials across multiple conflicting criteria such as recyclability, carbon footprint, durability, aesthetics, and manufacturing complexity. Furthermore, the inclusion of comparative analysis with six standalone MCDM models and a detailed sensitivity analysis demonstrates methodological robustness and result stability — features rarely explored together in existing literature. By focusing specifically on materials applicable to EV interiors, the study addresses a niche but rapidly growing area within green automotive design and adds a specialized, reproducible decision-support model that can inform both academic research and industrial application.

This research aims to develop a robust framework for selecting eco-friendly materials for EV interiors using Fuzzy-Entropy and TOPSIS MCDM techniques. The study focuses on identifying and evaluating sustainable materials while addressing uncertainties in the decision-making process. It prioritizes materials based on multiple criteria to recommend the most suitable alternatives [6]. To guide the direction of this study and address the identified research gaps, the following research questions have been formulated:

RQ1: What are the most relevant and comprehensive criteria for evaluating eco-friendly materials specifically suited for electric vehicle (EV) interiors in terms of sustainability, technical performance, user comfort, and economic feasibility?

RQ2: How can a hybrid Fuzzy MCDM model, integrating Fuzzy-Entropy and Fuzzy-TOPSIS, be effectively developed to handle uncertainty and subjectivity in the material selection process?

RQ3: Which eco-friendly material alternative ranks as the most suitable for EV interior applications when evaluated using the proposed Fuzzy-Entropy-TOPSIS model, and how do these results compare with other established MCDM techniques?

These questions form the foundation of the research, aiming to provide a structured, data-driven, and uncertainty-resilient decision-making approach to sustainable material selection in the automotive sector. These insights provide a structured approach to material selection, supporting the automotive industry's shift toward sustainable EV interiors.

The remainder of this paper is organized as follows. Section 2 reviews existing literature on eco-friendly materials for electric vehicle interiors and the application of MCDM methods in sustainable material selection. Section 3 outlines the research methodology, including the formation of expert groups, criteria selection, and the implementation of the Fuzzy-Entropy and Fuzzy-TOPSIS models. Section 4 presents the evaluation results, including the determination of criteria weights, material rankings, and a detailed sensitivity analysis. Section 5 discusses the findings and their implications in the context of sustainable automotive design, along with the comparative analysis with six other MCDM models. Section 5 also outlines the practical implications, limitations, and directions for future research. Finally, Section 6 concludes the study by summarizing its contributions and emphasizing its relevance to sustainable decision-making in the automotive sector.

1.1 Literature review

As the automotive industry shifts towards sustainability, EVs are becoming central to reducing the environmental footprint of transportation. A key aspect of this movement is the development and adoption of eco-friendly materials for EV interiors. This literature review explores various studies on eco-friendly materials in vehicle interiors, including their environmental benefits, technical feasibility, and user acceptance.

1.1.1 Eco-friendly materials for EV interiors

Conventional automotive materials, reliant on non-renewable resources, generate high emissions and pose disposal challenges. Traditionally, interiors use synthetic polymers for durability and cost-effectiveness, but this contributes to resource depletion and landfill waste [7,8]. EV manufacturers now prioritize eco-friendly materials to enhance sustainability and support circular economy practices by reducing virgin material use and promoting recycling. Research focuses on renewable, recyclable, and biodegradable materials for seats, dashboards, and door panels. Biomaterials like polylactic acid (PLA) from corn starch significantly cut carbon emissions compared to traditional plastics. Natural fibers such as hemp, flax, and jute, when combined with biodegradable resins, create strong, lightweight composites with improved thermal and acoustic insulation [9]. However, moisture and UV sensitivity affect durability. Advances in fiber treatment and hybridization have improved resistance, expanding their automotive applications. Ullah et al. [4] reviewed lightweight eco-friendly composite materials for automotive applications, stressing the potential of natural fiber composites such as flax, hemp, and kenaf reinforced polymers for reducing vehicle weight while maintaining structural integrity and sustainability. They highlighted that the use of bio-based polymers combined with natural fibers not only improves fuel efficiency by reducing weight but also promotes biodegradability and supports circular economy principles. These natural composites offer excellent thermal and acoustic insulation, making them suitable alternatives to conventional petroleum-based materials in EV interiors.

Another notable development was discussed by Veeman et al. [5], who analyzed the future prospects of natural fiber-reinforced polymeric composites for automotive tribological applications. Their study indicated that integrating natural fibers such as jute, hemp, and flax into polymer matrices can significantly reduce carbon emissions, improve thermal stability, and enhance wear resistance, which are critical for the performance of electric vehicle interior components. Moreover, the authors stressed that surface treatments and hybridization techniques can overcome natural fibers' inherent moisture absorption issues, thereby extending the lifespan and functional reliability of eco-friendly interior parts. In addition, Zahoor et al. [6] discussed the broader movement toward green mobility and highlighted how recycled and bio-based materials are transforming electric vehicle design. Their work revealed that manufacturers are increasingly adopting materials such as recycled PET fabrics and soy-based polyurethane foams to meet stringent sustainability regulations and consumer demand for greener products. The study emphasized that material selection strategies are evolving beyond mechanical performance toward a lifecycle-based approach, where recyclability, low VOC emissions, and minimal environmental footprints are becoming decisive factors for electric vehicle interiors.

Recycled materials help reduce EV interiors' ecological impact. Manufacturers are incorporating recycled plastics like PET from post-consumer bottles into seat fabrics, offering durability comparable to virgin materials while minimizing plastic waste. Advances in recycling allow post-consumer and industrial waste to be repurposed for automotive-grade components without performance loss [10]. Additionally, recyclable strategies, including “design for disassembly,” facilitate end-of-life material separation and recycling, supporting a circular economy. Collaboration across the supply chain is essential for effective disposal and recycling. Bio-based polymers, derived from soy, castor oil, and cellulose, are gaining traction for seat foams and dashboards. Soy-based polyurethane foams reduce carbon emissions by 24% compared to petroleum-based foams [7,8]. These alternatives lower toxicity and VOC emissions, enhancing vehicle cabin air quality. The shift to low-emission adhesives further boosts sustainability by reducing harmful emissions.

Despite progress, challenges persist. High costs due to limited production scales and supply chain inefficiencies remain a barrier, though economies of scale could lower costs as demand rises [4,5]. Consumer acceptance is another issue, as buyers may hesitate to pay a premium unless eco-friendly materials offer added comfort or aesthetic appeal. Research continues to validate the environmental and technical feasibility of natural fibers, bio-based polymers, and recycled materials, but cost efficiency and market adoption require further development [9,10]. Ongoing R&D, policy support, and consumer education will be key in overcoming these barriers, ensuring eco-friendly materials play a crucial role in the future of sustainable EVs.

1.1.2 MCDM applications in electric vehicle

With increasing emphasis on sustainability in the automotive industry, selecting eco-friendly materials for EV interiors is a complex challenge involving environmental impact, cost, recyclability, and aesthetics. MCDM methods provide a structured approach for evaluating materials, balancing these criteria effectively [6,7]. This review examines AHP, TOPSIS, and fuzzy MCDM methods in material selection, highlighting their strengths and applications. MCDM is widely recognized for addressing multi-criteria decision-making challenges in sustainable material selection. Krishankumar et al. [11] emphasize its role in integrating environmental, economic, and social criteria, allowing manufacturers to compare trade-offs among recyclability, cost, and carbon emissions. Studies by Yu et al. [12] highlight MCDM's importance in balancing technical properties like durability and comfort with sustainability. AHP and TOPSIS are particularly valued for their ability to assign weights to criteria, making them adaptable to evolving eco-friendly design priorities. AHP is a popular method due to its hierarchical structure, enabling systematic pairwise comparisons. Kurniadi and Ryu [13] used AHP to evaluate materials like recycled plastics and natural fibers based on recyclability, cost, and environmental impact, identifying natural fibers as an optimal choice. Similarly, Jeyanthi et al. [14] found AHP useful for integrating subjective expert opinions on aesthetics and comfort.

TOPSIS ranks materials by assessing their relative distance from an ideal solution. Dash et al. [15] used it to evaluate materials based on environmental impact, manufacturability, and recyclability, demonstrating its effectiveness in identifying balanced options. Soni et al. [16] highlighted its ability to incorporate qualitative and quantitative factors, ensuring alignment with consumer demands. Fuzzy MCDM methods handle uncertainty in material assessments by incorporating linguistic variables. Zadeh [17] applied fuzzy MCDM to evaluate hemp composites, soy-based polymers, and recycled fabrics, emphasizing its value in scenarios where precise data is unavailable. Fuzzy AHP and fuzzy TOPSIS further enhance decision-making by integrating fuzzy logic with traditional MCDM techniques. Ikram et al. [18] used fuzzy AHP to rank materials based on both quantitative (carbon emissions) and qualitative (consumer comfort) factors, improving accuracy in subjective evaluations.

Hybrid MCDM models combine multiple methods for enhanced decision-making. Kenger et al. [19] proposed a fuzzy AHP-TOPSIS model for selecting EV interior materials based on recyclability, emissions, and durability, capturing both subjective and objective factors. Ullah et al. [20] emphasized the importance of generalized fuzzy data in sustainability assessments, proposing a SWOT-based MCDM framework that integrates environmental, economic, and user-centric factors for sustainable transport solutions. Skosana et al. [21] provided a comprehensive review of natural fiber-reinforced polymeric composites, highlighting new innovations in biodegradable and recyclable materials suitable for automotive applications, and underscoring the importance of integrating material performance with ecological impacts. Similarly, Magabaleh et al. [22] demonstrated the effectiveness of combining multiple-criteria decision-making models with self-organizing maps to enhance the assessment of sustainable energy systems, illustrating the growing relevance of hybrid approaches in complex sustainability problems. In the context of fuzzy MCDM applications, recent studies have shown that hybrid models such as Fuzzy-Entropy-TOPSIS and Fuzzy-AHP-VIKOR have become increasingly popular for balancing subjective expert evaluations with objective data-driven criteria weighting, improving decision robustness in material selection problems.

These studies reinforce the need for decision-making frameworks that not only consider environmental and economic aspects but also address uncertainties inherent in qualitative attributes such as user comfort and aesthetic preferences. These models provide a comprehensive approach by integrating lifecycle assessment, manufacturing ease, and user satisfaction. MCDM methods have significantly advanced sustainable material selection in the automotive industry. AHP and TOPSIS offer reliable frameworks for prioritizing materials, while fuzzy MCDM effectively addresses uncertainties in subjective assessments. Hybrid models further enhance decision accuracy by incorporating multiple evaluation criteria. As demand for eco-friendly interiors grows, MCDM will continue to play a vital role in informed and balanced material selection.

1.1.3 Research gaps

The literature on MCDM methods for sustainable material selection in EV interiors reveals key research gaps, underscoring the need for an advanced framework [18,19,20]. Traditional MCDM methods like AHP and TOPSIS have been widely used [8,14,20] but struggle with uncertainty in evaluating qualitative attributes such as aesthetics, user comfort, and eco-friendliness. While fuzzy MCDM addresses uncertainty [3,11,17,19], limited studies integrate both quantitative and qualitative attributes holistically. Many rely on subjective expert weighting [21,22], which introduces bias, while entropy-based objective weighting remains underutilized in combination with fuzzy logic, leaving a gap in achieving balanced evaluations. Most existing research focuses on general automotive materials or conventional vehicles, overlooking EVs' unique sustainability demands [12]. EV interiors require lightweight, recyclable materials, yet studies inadequately capture qualitative factors like aesthetic appeal and user comfort. Though fuzzy MCDM helps address subjective aspects, few studies integrate fuzzy logic with entropy-based weighting to refine these assessments, limiting the accuracy of consumer and expert evaluations.

Hybrid MCDM models such as fuzzy AHP-TOPSIS have been explored but often focus narrowly on environmental or economic aspects rather than integrating diverse attributes crucial for EV interiors. Most studies on sustainable automotive materials target conventional vehicles, neglecting EVs' distinct interior requirements—such as low-emission production and durability—highlighting the need for a tailored framework [2,10]. With the automotive industry's shift toward circular economy principles, recyclability, life-cycle impact, and ease of disassembly are becoming vital criteria. However, most studies focus on initial material properties rather than end-of-life sustainability [5,19]. Research on MCDM frameworks incorporating circular economy principles in EV interiors remains limited. Hybrid models integrating entropy with traditional MCDM techniques like TOPSIS are rarely explored. While some studies employ hybrid MCDM, they either lack fuzzy components or apply entropy independently of subjective assessments [11,15,17]. A robust model combining entropy-based objective weighting with fuzzy TOPSIS could better rank eco-friendly materials, balancing objective data with fuzzy logic's flexibility in handling qualitative attributes.

1.1.4 Novelty

This research fills critical gaps by introducing a novel MCDM framework that integrates fuzzy logic, entropy-based weighting, and TOPSIS, making significant contributions to sustainable automotive material selection. Unlike existing models designed for general automotive applications, this study tailors fuzzy MCDM methods specifically for eco-friendly EV interior materials. By addressing key sustainability challenges, the framework incorporates criteria such as reducing carbon footprints and enhancing recyclability. Notably, this is among the first studies to integrate entropy-based objective weighting with fuzzy logic and TOPSIS for EV material selection, balancing data-driven assessments (e.g., durability, emissions, cost) with subjective evaluations (e.g., user comfort, aesthetics). The proposed model effectively handles subjectivity in criteria like consumer comfort, aesthetics, and eco-friendliness, where conventional MCDM methods face limitations. Fuzzy logic enables quantification of subjective preferences while integrating technical and user-centric criteria. Entropy-based weighting strengthens the framework by objectively determining criteria weights through data variability while fuzzy logic captures expert insights. This hybrid approach produces criteria weights that are both data-driven and expert-informed, enhancing material evaluation robustness compared to models relying solely on subjective weighting.

Aligning with sustainability trends, this study incorporates lifecycle-based criteria such as recyclability, end-of-life disassembly, and minimal waste generation, supporting circular economy principles. While many studies focus only on initial material properties, this research emphasizes materials that promote sustainability throughout their lifecycle. The hybrid Fuzzy Entropy-TOPSIS approach refines criteria weighting and material ranking by combining entropy's objectivity with fuzzy TOPSIS's ability to handle subjective uncertainties. This ensures a balanced decision-making approach that improves accuracy in selecting eco-friendly materials meeting both technical and consumer-oriented requirements. The developed Fuzzy Integrated Entropy-TOPSIS model serves as a valuable decision-support tool for EV manufacturers in selecting sustainable materials. Beyond automotive applications, the proposed framework is adaptable for use in various sustainability-driven industries. By integrating data-driven entropy-based weighting with fuzzy MCDM, this study sets a new standard for robust and adaptable decision-making. Additionally, the incorporation of circular economy principles encourages future research to develop more specialized MCDM models that address evolving sustainability challenges across multiple sectors.

2 Materials and methods

The methodology section presents a structured approach for applying Fuzzy MCDM [17] techniques to select eco-friendly materials for EV interiors. This study integrates Fuzzy Entropy [22] and Fuzzy TOPSIS [23] to address uncertainties and subjective judgments in material evaluation. Four eco-friendly materials are assessed using nine criteria: recyclability, durability, strength, comfort, aesthetic appeal, carbon footprint, price, energy requirements, and manufacturing complexity. The Fuzzy Entropy method quantifies the uncertainty associated with each criterion to derive objective weights. Fuzzy TOPSIS then ranks the materials based on their weighted performance, identifying the most sustainable alternative [22,23]. This hybrid approach ensures a transparent decision-making framework, guiding the automotive industry toward sustainability. The following steps detail the execution of this decision-making process.

- Understanding the goal: Define the objective and scope of the fuzzy MCDM analysis in the context of selecting eco-friendly materials for EV interiors.
- Formation of expert teams: Create three groups based on expertise and roles in the project.
- Criteria selection and material alternatives: Identify and prioritize key criteria for material selection.
- Defining fuzzy MCDM model parameters: Establish fuzzy logic scales, membership functions, and pairwise comparison methods.
- Data collection and model validation: Plan data sources, validation techniques, and review processes.

2.1 Formation of expert committee

Selecting eco-friendly materials for EV interiors is essential for sustainable automotive design, impacting both environmental footprint and user experience. Factors such as recyclability and aesthetic appeal play a crucial role in material selection. To navigate these complexities, this study applies fuzzy MCDM methods to evaluate and prioritize materials. A multidisciplinary team of experts in environmental science, engineering design, and data analysis collaborates to develop a fuzzy MCDM framework. This approach balances environmental, technical, and user-centric criteria, creating a comprehensive tool for material selection aligned with EV sustainability goals. To ensure expert-driven decision-making, a committee of nine highly experienced members has been formed, specializing in relevant fields. For a structured evaluation, the team is divided into three groups, each focusing on a specific aspect of the project, as presented in Table 1.

Table 1. Formation of expert committee *(Source: Author's own elaboration)*

Expert member	Designation	Years of experience	Individual role	Team role
Group A: Environmental and materials science team				
EM 1	Senior environmental scientist	15	Team Leader; Evaluates environmental impacts, focusing on recyclability, emissions, and renewability.	This team will evaluate the environmental impacts of various materials, focusing on recyclability, carbon emissions, and the renewable nature of the sources. They will guide the criteria development around eco-friendliness and sustainable sourcing.
EM 2	Materials scientist	12	Assesses sustainable polymers and material properties related to eco-friendliness.	
EM 3	Expert in Renewable Resources	20	Provides expertise on recycling technologies and renewable material sourcing.	
Group B: Engineering and design team				
EM 4	Senior automotive interior designer	18	Team Leader; Oversees evaluation of design suitability and user experience.	This group will assess the functional and aesthetic properties of materials, such as durability, tactile quality, and visual appeal. Their inputs will refine criteria for technical feasibility and user experience
EM 5	Mechanical engineer	10	Examines technical feasibility and material compatibility with automotive manufacturing.	

Expert member	Designation	Years of experience	Individual role	Team role
EM 6	Product designer	8	Specializes in biomaterials, focusing on comfort and aesthetic aspects for user appeal.	aspects, ensuring selected materials are suitable for automotive applications.
Group C: Fuzzy MCDM and data analysis team				
EM 7	Data scientist	14	Team Leader; Designs and implements fuzzy MCDM model for decision-making.	This group is tasked with designing the fuzzy MCDM model, establishing criteria, and implementing fuzzy logic parameters. They will ensure that qualitative judgments on eco-friendliness and technical performance are accurately translated into the fuzzy MCDM framework.
EM 8	Data analyst	7	Supports model building and analysis with expertise in fuzzy logic.	
EM 9	Decision science specialist	9	Provides input on sustainable decision models, emphasizing data integration and validation.	

2.2 Criteria selection and material alternatives

Selecting the right criteria is crucial in the MCDM process as it directly affects the evaluation and ranking of eco-friendly materials for EV interiors. This research identifies nine key criteria to ensure a comprehensive assessment of sustainability, performance, and feasibility: recyclability, durability, strength, comfort, aesthetic appeal, carbon footprint, price, energy requirements, and complexity in manufacturing [6,23]. Their significance and contributions to this study are detailed in Table 2. A brainstorming session was conducted to identify critical factors for material selection. Each team contributed insights, leading to a consolidated list of criteria. The key discussions and justifications for these criteria are elaborated in Table 2.

The selection of evaluation criteria was based on a combination of an extensive literature review and expert consultation. Academic sources, including recent studies on sustainable materials in automotive design and applications of MCDM in green manufacturing, were analyzed to identify commonly used performance indicators. This preliminary list was then validated and finalized through a structured brainstorming process with three expert groups comprising professionals in automotive materials engineering, sustainability research, and decision sciences. The direction of each criterion was clearly defined to ensure proper normalization and evaluation. Specifically, recyclability, durability, strength, comfort and aesthetic appeal were treated as benefit-oriented criteria - meaning higher values are preferred. Conversely, carbon footprint, price, energy requirements, and complexity in manufacturing were considered cost-oriented criteria — where lower values are more desirable. This classification was applied consistently throughout the Fuzzy-Entropy and Fuzzy-TOPSIS processes to ensure methodological accuracy.

Table 2. Selected parameters and their significances *(Source: Author's own elaboration)*

Categories	Parameters	Definition	Importance	Contribution
Environmental impact	Recyclability [4,8,13]	Recyclability refers to the ability of a material to be reprocessed and reused at the end of its life cycle.	High recyclability reduces waste and conserves resources by enabling materials to be reincorporated into the production cycle, thus supporting circular economy principles. It is crucial for minimizing environmental impact and achieving sustainability goals.	Led by group A
	Carbon footprint [3,7,9,22]	Carbon footprint is the total amount of greenhouse gases emitted directly or indirectly during the material's lifecycle.	Minimizing the carbon footprint is essential for reducing the environmental impact of materials. Lower carbon emissions contribute to the overall sustainability and climate change mitigation efforts of the automotive industry.	
	Energy requirements [8,16]	Energy requirements pertain to the amount of energy needed to produce, process, and incorporate the material into the vehicle interior.	Materials with lower energy requirements contribute to reducing the overall energy consumption and environmental footprint of the manufacturing process. This criterion aligns with the goals of energy efficiency and sustainability.	
Technical feasibility	Durability [1,12]	Durability measures the material's ability to withstand wear, pressure, or damage	Durable materials ensure the longevity of vehicle interiors, reducing the need for frequent replacements and associated costs and environmental impacts. Durability	Led by group B

Categories	Parameters	Definition	Importance	Contribution
		over time.	also enhances the perceived quality and value of the vehicle.	
	Strength [10,15,19]	Strength is the material’s ability to resist deformation and maintain structural integrity under stress.	Strong materials contribute to the safety and structural stability of the vehicle interior components, ensuring they can endure various mechanical stresses during the vehicle's lifecycle.	
	Complexity in manufacturing [18,20,21]	Complexity in manufacturing refers to the challenges and technical difficulties associated with processing and integrating the material into the vehicle interior.	Materials that are easier to manufacture and integrate reduce production time, costs, and potential defects. Simplicity in manufacturing also enhances scalability and operational efficiency.	
User-centric factors	Comfort [2,5]	Comfort encompasses the material’s ability to provide a pleasant and ergonomic experience for occupants.	Comfortable materials improve the overall user experience, influencing customer satisfaction and acceptance. Factors such as softness, temperature regulation, and tactile feel are critical in evaluating comfort.	
	Aesthetic appeal [6,11,23]	Aesthetic appeal refers to the visual and tactile attractiveness of the material.	Materials with high aesthetic appeal enhance the interior design and marketability of the vehicle. The look and feel of the materials contribute significantly to the perceived luxury and quality of the vehicle.	
Cost-effectiveness	Price [10,14,16]	Price refers to the cost of acquiring and utilizing the material in the manufacturing process.	Cost-effectiveness is a key factor in material selection, impacting the overall production budget and vehicle pricing. Balancing cost with performance and sustainability is essential for commercial viability.	Led by group C

The nine criteria chosen — recyclability, durability, strength, comfort, aesthetic appeal, carbon footprint, price, energy requirements, and complexity in manufacturing — were identified through a structured brainstorming process involving multidisciplinary experts in environmental science, automotive engineering, and decision science. These criteria were specifically selected because they collectively address the core dimensions of sustainability, technical feasibility, economic viability, and user acceptance, all of which are critical for the successful integration of eco-friendly materials in electric vehicle interiors [25]. Recyclability and carbon footprint are directly tied to environmental impact, ensuring that materials contribute to the circular economy and reduce greenhouse gas emissions. Durability and strength influence the longevity of interior components, minimizing the frequency of replacement and thus conserving resources over the product’s lifecycle. Comfort and aesthetic appeal were included because materials must not only be sustainable but also acceptable to consumers to promote widespread adoption of green technologies. Price and complexity in manufacturing were deliberately incorporated to balance environmental benefits with practical economic considerations, acknowledging that affordability and ease of production are essential for large-scale industrial implementation [26]. Furthermore, the inclusion of energy requirements ensures that materials selected are not only sustainable in their end use but also during their production processes. By integrating these environmental, technical, and user-centric factors within a Fuzzy MCDM framework, this study provides a holistic and practical approach to sustainable material selection.

Specifically, the majority of the selected criteria are benefit-oriented, meaning that higher values are desirable, as they contribute positively to the sustainability and performance of the EV interiors. The five benefit-oriented criteria include recyclability, durability, strength, comfort and aesthetic appeal [27]. On the other hand, four criteria — carbon footprint, price, energy requirements and complexity in manufacturing — are cost-oriented, where lower values are preferred because they reduce carbon emissions, production expenses, resource consumption, and technical difficulties. This classification was crucial during the normalization stage of both the entropy and TOPSIS methods, where different normalization equations were applied based on whether the criterion was to be maximized or minimized.

This study establishes a comprehensive framework for selecting eco-friendly materials for EV interiors by evaluating environmental impact, performance, economic factors, and manufacturing feasibility. It examines four promising materials - Bamboo Fiber Composite (BFC), Recycled Polyethylene Terephthalate (PET), Hemp Fiber Composite (HFC), and Biodegradable Polylactic Acid (PLA) - based on nine conflicting criteria, including recyclability, durability, strength, comfort, aesthetics, carbon footprint, cost, energy requirements, and manufacturing complexity [25]. These materials were chosen for their sustainability potential while maintaining the required performance and aesthetic standards. Using Fuzzy Entropy and TOPSIS MCDM techniques, this research ensures a structured and robust evaluation, ultimately guiding the selection of the most sustainable material for EV interiors. Table 3 summarizes the relevance of these materials to the identified criteria.

Table 3. Comparative analysis of eco-friendly material alternatives for EV interiors based on various criteria *(Source: Author's own elaboration)*

Criteria	BFC	PET	HFC	PLA
Recyclability	High (biodegradable, recyclable composite)	High (multiple recyclability, supports closed-loop)	High (biodegradable, recyclable composite)	Variable (compostable industrially, limited conventional recycling)
Durability	Very good (moisture and pest resistant with treatment)	Excellent (resistant to wear, chemicals, UV light)	Very good (resistant to wear, biodegradation)	Good (dependent on formulation and conditions)
Strength	High (comparable to synthetic composites)	High (suitable for structural and non-structural)	Adequate (requires less reinforcement than other natural fibers)	Adequate (may require reinforcement for structural applications)
Comfort	Natural feel, good thermal properties	Engineered for enhanced comfort	Pleasant tactile feel, good insulation	Flexible, engineered for comfort
Aesthetic Appeal	Attractive natural appearance, customizable finishes	Versatile, various finishes and colors	Attractive natural look, enhanced with treatments	Similar to conventional plastics, various finishes and colors
Carbon Footprint	Low (rapid CO2 absorption during growth)	Lower than virgin plastics	Low (CO2 absorption during growth, minimal pesticides/fertilizers)	Low (derived from renewable resources, compostable)
Price	Competitive (varies based on processing/treatment)	Variable (often lower than virgin materials)	Reasonable (varies based on fiber processing/composite formulation)	Higher than conventional plastics (decreasing with production scale)
Energy Requirements	Low (quick growth, minimal energy to harvest)	Moderate (energy savings compared to virgin PET)	Low (energy-efficient cultivation and processing)	Moderate (lower raw material extraction, variable production energy)
Complexity in Manufacturing	Moderate (requires specific treatments)	Low to moderate (adaptable to existing processes)	Moderate (attention to fiber-matrix bonding, consistency)	Moderate (adjustments in processing techniques needed)

2.3 Entropy

The Entropy MCDM objective weighting technique is a systematic approach that evaluates and assigns weights to criteria based on their inherent information content. Rooted in information theory, entropy quantifies uncertainty, with lower entropy indicating higher informativeness and leading to greater weight assignment [22]. Unlike subjective methods that rely on expert judgment, entropy provides an objective, data-driven mechanism that minimizes human bias. By assessing the variation in alternatives across each criterion, it identifies the most discriminative factors, ensuring a more balanced evaluation [20,26]. Entropy stands out due to its objectivity, consistency, and transparency. It eliminates subjective bias by deriving weights solely from decision matrix data, ensuring stability across different scenarios. Compared to traditional methods like AHP and BWM, which depend on expert preferences, entropy maintains reliability across various decision-making contexts [14,29]. Its mathematically rigorous yet straightforward approach makes it widely applicable across fields such as engineering, finance, environmental management, and healthcare. The superiority of entropy over other weighting methods lies in its evidence-based, data-driven nature. Unlike CRITIC or other complex statistical models, entropy's straightforward computations enhance clarity and trustworthiness. It aligns with contemporary decision-making practices by prioritizing empirical evidence over subjective opinions, making it a preferred method for robust evaluations [8,25]. Table 4 presents a comparative analysis of objective and subjective MCDM weighting techniques, highlighting their respective strengths and limitations.

Table 4. Strengths and limitations comparison of various objective and subjective MCDM weighting techniques
(Source: Author's own elaboration)

MCDM Methods	Strengths	Limitations
Objective MCDM weighting techniques		
Entropy [20,22]	• Objectivity: Derives weights solely from the data, minimizing subjective bias. • Consistency: Provides consistent results across different decision-making scenarios.	• Sensitivity to data: Requires sufficient and accurate data for reliable weight determination. • Lack of flexibility: May not capture qualitative aspects that influence decision-making.
CRITIC [22]	• Considers interactions: Accounts for interdependencies between criteria. • Objective: Based on statistical analysis, reducing subjective influence.	• Complexity: Requires complex computations and statistical analysis, making it less accessible for some users. • Data intensive: Relies on extensive data inputs, which may not always be available or feasible.
MEREC [18,19]	• Objectivity: Evaluates criteria weights based on categorical ratings, reducing subjectivity. • Simplicity: Easy to understand and apply, particularly in qualitative decision contexts.	• Limited precision: May not capture nuanced differences between criteria due to categorical rating scales. • Lack of sensitivity: May not adequately distinguish between criteria with similar ratings.
Subjective MCDM weighting techniques		
AHP [13,16,17]	• Structured approach: Provides a hierarchical framework for decision analysis. • Flexibility: Allows decision-makers to incorporate qualitative factors and expert judgments.	• Subjectivity: Relies heavily on subjective judgments, leading to potential bias. • Complexity: Requires significant time and effort to gather expert opinions and perform pairwise comparisons.
Subjective MCDM weighting techniques		
BWM [13,14,17]	• Relative comparison: Focuses on identifying the best and worst criteria, simplifying the decision process. • Intuitive: Easy to understand and implement, even for non-experts.	• Limited scale: May not capture the relative importance of criteria beyond best and worst rankings. • Vulnerable to anchoring bias: Results may be influenced by the initial selection of best and worst criteria.
SWARA [24,25,28,31]	• Systematic: Provides a step-by-step approach to criteria weighting, enhancing transparency. • Flexibility: Allows for iterative adjustments and refinements in the weighting process.	• Time-consuming: Requires multiple iterations and comparisons, which can be labor-intensive. • Subjectivity: Still subject to the biases and preferences of decision-makers, particularly in the selection of reference alternatives.

Objective MCDM weighting techniques offer objectivity and consistency but may require extensive data and lack flexibility. Subjective techniques, on the other hand, allow for qualitative inputs and expert judgments but are susceptible to bias and may be more complex to implement. The choice between these approaches depends on the specific decision context, available data, and the preferences of decision-makers [24,25]. The steps of entropy methods may be presented as follows.

Construct the decision matrix (Step 1): Let 'X' be the decision matrix with 'm' alternatives and 'n' criteria. The element 'x_{ij}' in Eq. (1) represents the performance value of the i-th alternative with respect to the j-th criterion.

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

Normalize the decision matrix (Step 2): Normalize the decision matrix to transform the different scales of the criteria into a comparable one. Based on the max and min criteria, the normalized values '$r_{ij}^{\max(E)}$' and '$r_{ij}^{\min(E)}$' are calculated using Eq. (2) and Eq. (3) respectively.

$$r_{ij}^{\max(E)} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad (2)$$

$$r_{ij}^{\min(E)} = \frac{\frac{1}{x_{ij}}}{\sum_{i=1}^{m} \frac{1}{x_{ij}}} \quad (3)$$

Calculate the entropy of each criterion (Step 3): Entropy 'E_j' measures the degree of uncertainty or disorder associated with the j-th criterion. It is calculated using the following given in Eq. (4). Where, 'k' is a constant and defined as $k = \frac{1}{\ln(m)}$ to ensure that $0 \leq E_j \leq 1$.

$$E_j = -k \sum_{i=1}^{m} r_{ij} \ln(r_{ij}) \tag{4}$$

Determine the degree of diversification (redundancy) for each criterion (Step 4): The degree of diversification 'd_j' (also called the weight or discrimination measure) is calculated using Eq. (5).

$$d_j = |1 - E_j| \tag{5}$$

Calculate the weight of each criterion (Step 5): The weight 'w_j' of each criterion is determined by normalizing the degrees of diversification using Eq. (6).

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{6}$$

2.4 TOPSIS

TOPSIS, developed by Lai et al. [23] in the 1990s, is a widely used MCDM method for ranking alternatives based on their relative proximity to an ideal solution. This technique is particularly effective in handling multiple conflicting criteria by identifying an ideal solution with the best values for each criterion and a negative-ideal solution with the worst values [2,8]. Alternatives are ranked based on their Euclidean distance from these solutions, with the best option being closest to the ideal and farthest from the negative-ideal solution [30,31]. TOPSIS provides a structured approach to decision-making by considering both optimal and worst-case scenarios, ensuring a balanced evaluation of alternatives [20]. It is simple to implement, making it accessible to decision-makers across various domains. Its ability to handle both qualitative and quantitative criteria makes it highly versatile, allowing applications in engineering, finance, management, and healthcare [2,8,20]. The method's structured steps ensure a transparent and rational decision-making process, enhancing its effectiveness in MCDM applications.

Construct the decision matrix (Step 1): TOPSIS method also starts with the formation of a decision matrix as shown in Eq. (1).

Normalize the decision matrix (Step 2): Normalize the decision matrix to transform the different scales of the criteria into a comparable one. The normalized values 'r_{ij}^{T}' is calculated using Eq. (7).

$$r_{ij}^{T} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{7}$$

Calculate the weighted normalized decision matrix (Step 3): The weighted normalized decision matrix (v_{ij}) is computed using Eq. (8) by multiplying each element (r_{ij}^{T}) of the normalized decision matrix by the corresponding criterion weight (w_j).

$$v_{ij} = r_{ij}^{T} \times w_j \tag{8}$$

Determine the positive ideal and negative ideal solutions (Step 4): The positive ideal solution and the negative ideal solution are defined by Eq. (9) and Eq. (10) as follows.

$$A^{+} = \left\{ \left(\max_{i} v_{ij} \text{ if } j \text{ is a benefit criterion}, \min_{i} v_{ij} \text{ if } j \text{ is a cost criterion} \right) \middle| j = 1, 2, 3 \ldots, n \right\} \tag{9}$$

$$A^{-} = \left\{ \left(\min_{i} v_{ij} \text{ if } j \text{ is a benefit criterion}, \max_{i} v_{ij} \text{ if } j \text{ is a cost criterion} \right) \middle| j = 1, 2, 3 \ldots, n \right\} \tag{10}$$

Calculate the separation measures (Step 5): The separation measure from the positive ideal solution (S_i^{+}) and the separation measure from the negative ideal solution (S_i^{-}) for each alternative are calculated using Eq. (11) and Eq. (12) as follows.

$$S_i^{+} = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^{+}\right)^2} \tag{11}$$

$$S_i^{-} = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^{-}\right)^2} \tag{12}$$

Calculate the relative closeness coefficient (RCC) to the ideal solution (Step 6): The relative closeness of the *i-th* alternative to the ideal solution (C_i^{*}) is calculated using Eq. (13).

$$C_i^{*} = \frac{S_i^{-}}{S_i^{+} + S_i^{-}} \tag{13}$$

Rank the alternatives (Step 7): Rank the alternatives based on the RCC values. The alternative with the highest RCC value is considered the best choice.

3 Results and discussion

The next section presents the mathematical analysis of four EV interior material alternatives based on nine evaluation criteria. Initially, the Entropy method is applied in a fuzzy environment to determine criteria weights, followed by the application of TOPSIS to rank the material options. The process follows structured steps to achieve the study's objectives. First, a scale is established by committee members, as shown in Table 5. The expert groups assess the four alternatives using qualitative expressions, which are documented in Table 6. These linguistic terms are then converted into numerical values using triangular fuzzy numbers (TFNs) based on the fuzzy scale in Table 5. A graphical representation of the TFN distributions is provided in Fig. 1 to illustrate the data transformation.

Table 5. Scale conversion of linguistic terms into TFNs *(Source: Committee of expert members)*

Linguistic terms	Designation	Numeric values	TFNs
Very Low	VL	1	1,1,2
Low	L	3	2,3,4
Moderate	M	5	4,5,6
High	H	7	6,7,8
Very High	VH	9	8,9,9

Table 6. Qualitative performance rating of the alternatives *(Source: Committee of expert members)*

Expert team 1									
Alternatives/Criteria	R	D	S	C	AA	CF	P	ER	CM
BFC	M	H	H	H	H	L	M	M	H
	4,5,6	6,7,8	6,7,8	6,7,8	6,7,8	2,3,4	4,5,6	4,5,6	6,7,8
PET	H	H	M	M	M	M	L	M	L
	6,7,8	6,7,8	4,5,6	4,5,6	4,5,6	4,5,6	2,3,4	4,5,6	2,3,4
HFC	M	H	H	H	H	L	M	M	H
	4,5,6	6,7,8	6,7,8	6,7,8	6,7,8	2,3,4	4,5,6	4,5,6	6,7,8
PLA	H	M	M	M	M	L	M	M	M
	6,7,8	4,5,6	4,5,6	4,5,6	4,5,6	2,3,4	4,5,6	4,5,6	4,5,6
Expert team 2									
Alternatives/Criteria	R	D	S	C	AA	CF	P	ER	CM
BFC	M	H	M	M	H	M	H	M	VH
	4,5,6	6,7,8	4,5,6	4,5,6	6,7,8	4,5,6	6,7,8	4,5,6	8,9,9
PET	H	VH	H	M	H	L	VL	L	VL
	6,7,8	8,9,9	6,7,8	4,5,6	6,7,8	2,3,4	1,1,2	2,3,4	1,1,2
HFC	M	M	H	H	M	L	M	M	VH
	4,5,6	4,5,6	6,7,8	6,7,8	4,5,6	2,3,4	4,5,6	4,5,6	8,9,9
PLA	M	L	M	M	M	L	H	H	M
	4,5,6	2,3,4	4,5,6	4,5,6	4,5,6	2,3,4	6,7,8	6,7,8	4,5,6
Expert team 3									
Alternatives/Criteria	R	D	S	C	AA	CF	P	ER	CM
BFC	L	M	M	M	M	L	M	L	VH
	2,3,4	4,5,6	4,5,6	4,5,6	4,5,6	2,3,4	4,5,6	2,3,4	8,9,9
PET	M	VH	H	H	H	VL	VL	L	VL
	4,5,6	8,9,9	6,7,8	6,7,8	6,7,8	1,1,2	1,1,2	2,3,4	1,1,2
HFC	L	M	H	H	L	L	L	M	VH
	2,3,4	4,5,6	6,7,8	6,7,8	2,3,4	2,3,4	2,3,4	4,5,6	8,9,9
PLA	M	L	L	H	H	L	H	H	H
	4,5,6	2,3,4	2,3,4	6,7,8	6,7,8	2,3,4	6,7,8	6,7,8	6,7,8

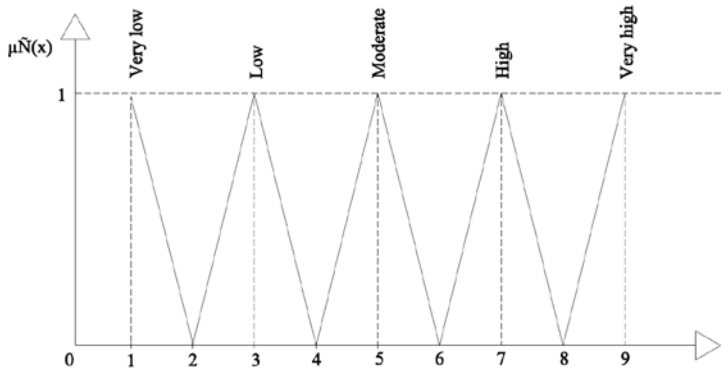

Fig. 1. Representation of triangular fuzzy number *(Source: Author's own elaboration)*

Step 2: The decisions made by the three expert teams are aggregated using Eq. (14) to achieve the fuzzy decision matrix shown in Table 7. Similarly, the TFNs in Table 7 are defuzzified using Eq. (15) to obtain the final decision matrix shown in Table 8.

If there are two fuzzy numbers say, $\widetilde{N_1}$ = (a_1, b_1, c_1) and $\widetilde{N_2}$ = (a_2, b_2, c_2), then these two fuzzy numbers can be aggregated using Eq. (14).

$$\widetilde{F_1} = (f_1, f_2, f_3) = (\min a_k, \tfrac{1}{2}\textstyle\sum_{k=1}^{2} b_k, \max c_k) \quad \text{(where, k = 1,2)} \tag{14}$$

Now, $\widetilde{N_1}$ = (a_1, b_1, c_1) can be defuzzified using Eq. (15).

$$D_1 = \frac{a_1+b_1+c_1}{3} \tag{15}$$

Table 7. Aggregated fuzzy decision matrix *(Source: Author's own elaboration)*

Alternatives	R	D	S	C	AA	CF	P	ER	CM
BFC	2,4.3333,6	4,6.3333,8	4,5.6667,8	4,5.6667,8	4,6.3333,8	2,3.6667,6	4,5.6667,8	2,4.3333,6	6,8.3333,9
PET	4,6.3333,8	6,8.3333,9	4,6.3333,8	4,5.6667,8	4,6.3333,8	1,3,6	1,1.6667,4	2,3.6667,6	1,1.6667,4
HFC	2,4.3333,6	4,5.6667,8	6,7,8	6,7,8	2,5,8	2,3,4	2,4.3333,6	4,5,6	6,8.3333,9
PLA	4,5.6667,8	2,3.6667,6	2,4.3333,6	4,5.6667,8	4,5.6667,8	2,3,4	4,6.3333,8	4,6.3333,8	4,5.6667,8

Table 8. Final decision matrix *(Source: Author's own elaboration)*

Nature	Max	Max	Max	Max	Max	Min	Min	Min	Min
Alternatives	R	D	S	C	AA	CF	P	ER	CM
BFC	4.1111	6.1111	5.8889	5.8889	6.1111	3.8889	5.8889	4.1111	7.7778
PET	6.1111	7.7778	6.1111	5.8889	6.1111	3.3333	2.2222	3.8889	2.2222
HFC	4.1111	5.8889	7	7	5	3	4.1111	5	7.7778
PLA	5.8889	3.8889	4.1111	5.8889	5.8889	3	6.1111	6.1111	5.8889

Step 3: Normalization process is carried out following step 2 of the entropy method to stabilize the performance values using Eq. (2) and Eq. (3) according to the nature of the criteria indicated in Table 8. The normalized values are evaluated in Table 9.

Table 9. Normalized performance values (entropy) *(Source: Author's own elaboration)*

Alternatives	R	D	S	C	AA	CF	P	ER	CM
BFC	0.2033	0.2582	0.2548	0.2387	0.2644	0.2101	0.1654	0.2815	0.1466
PET	0.3022	0.3286	0.2644	0.2387	0.2644	0.2451	0.4383	0.2976	0.5131
HFC	0.2033	0.2488	0.3029	0.2838	0.2163	0.2724	0.2369	0.2315	0.1466
PLA	0.2912	0.1643	0.1779	0.2387	0.2548	0.2724	0.1594	0.1894	0.1936

Step 4: Similarly, step 3 to step 5 of the entropy method have been followed to evaluate the entropy values, degree of diversification and the criteria weights applying Eq. (4) to Eq. (6). The respective weights of nine criteria are calculated and presented in Table 10.

Table 10. Evaluation of criteria weights *(Source: Author's own elaboration)*

Alternatives	R	D	S	C	AA	CF	P	ER	CM
BFC	-0.3239	-0.3496	-0.3484	-0.3420	-0.3517	-0.3278	-0.2976	-0.3568	-0.2815
PET	-0.3616	-0.3657	-0.3517	-0.3420	-0.3517	-0.3446	-0.3615	-0.3607	-0.3424
HFC	-0.3239	-0.3461	-0.3618	-0.3574	-0.3312	-0.3542	-0.3412	-0.3387	-0.2815

Alternatives	R	D	S	C	AA	CF	P	ER	CM
PLA	-0.3593	-0.2968	-0.3071	-0.3420	-0.3484	-0.3542	-0.2927	-0.3151	-0.3179
Sum	-1.3686	-1.3582	-1.3690	-1.3833	-1.3831	-1.3809	-1.2930	-1.3714	-1.2233
E_j	0.9873	0.9797	0.9875	0.9979	0.9977	0.9961	0.9327	0.9892	0.8824
$d_j = 1\text{-}E_j$	0.0127	0.0203	0.0125	0.0021	0.0023	0.0039	0.0673	0.0108	0.1176
Weight (w_j)	0.0511	0.0813	0.0499	0.0086	0.0094	0.0155	0.2697	0.0431	0.4715
Weight %	5.11	8.13	4.99	0.86	0.94	1.55	26.97	4.31	47.15

Step 5: Now, TOPSIS method has been applied to select the optimum alternative and to prescribe the preference ranking order of the alternatives. TOPSIS method also starts with a decision matrix as shown in Table 8.

Step 6: TOPSIS method follows vector normalization as per Eq. (7). The normalized values are shown in Table 11.

Table 11. Normalized matrix (TOPSIS) *(Source: Author's own elaboration)*

Weights	0.0511	0.0813	0.0499	0.0086	0.0094	0.0155	0.2697	0.0431	0.4715
Alternatives	R	D	S	C	AA	CF	P	ER	CM
BFC	0.3996	0.5029	0.5014	0.4760	0.5272	0.5847	0.6078	0.4232	0.6137
PET	0.5940	0.6401	0.5204	0.4760	0.5272	0.5012	0.2294	0.4003	0.1753
HFC	0.3996	0.4847	0.5960	0.5658	0.4313	0.4511	0.4243	0.5147	0.6137
PLA	0.5724	0.3201	0.3501	0.4760	0.5080	0.4511	0.6308	0.6291	0.4647

Step 7: The weighted values shown in Table 12 are calculated using Eq. (8).

Table 12. Weighted normalized matrix *(Source: Author's own elaboration)*

Alternatives	R	D	S	C	AA	CF	P	ER	CM
BFC	0.0204	0.0409	0.0250	0.0041	0.0049	0.0091	0.1640	0.0182	0.2894
PET	0.0303	0.0520	0.0260	0.0041	0.0049	0.0078	0.0619	0.0173	0.0827
HFC	0.0204	0.0394	0.0298	0.0048	0.0040	0.0070	0.1145	0.0222	0.2894
PLA	0.0292	0.0260	0.0175	0.0041	0.0048	0.0070	0.1701	0.0271	0.2191
Ideal best	0.0303	0.0520	0.0298	0.0048	0.0049	0.0070	0.0619	0.0173	0.0827
Ideal worst	0.0204	0.0260	0.0175	0.0041	0.0040	0.0091	0.1701	0.0271	0.2894

Step 8: From step 7 identify the ideal best and worst values for each criterion according to Eq. (9) and Eq. (10) as indicated in Table 13. Now, the positive and negative distances from the ideal solution are calculated using Eq. (11) and Eq. (12) and presented in Table 13.

Step 9: The RCC values of each alternative is calculated using Eq. (13) and shown in Table 13.

Step 10: Finally, rating of the alternatives has been done in Table 13 according to the RCC values.

Table 13. Rating of alternatives *(Source: Author's own elaboration)*

Alternatives	S+	S-	RCC	%	RANK
BFC	0.2311	0.0199	0.0793	7.93	4
PET	0.0039	0.2354	0.9836	98.36	1
HFC	0.2139	0.0588	0.2156	21.56	3
PLA	0.1768	0.0709	0.2861	28.61	2

3.1 Discussion

The growing demand for sustainable automotive solutions has necessitated a more rigorous evaluation of eco-friendly materials for EV interiors. This study applied a Fuzzy-MCDM framework, integrating Fuzzy-Entropy and Fuzzy-TOPSIS methods, to assess and prioritize materials based on multiple criteria. The incorporation of fuzzy logic into MCDM techniques was essential in addressing the inherent uncertainty and subjectivity in evaluating diverse selection factors. Through the Fuzzy-Entropy method, the study determined the relative importance of each criterion, as shown in Table 10. The results indicate that complexity in manufacturing (CM) and price (P) held the highest weights at 47.15% and 26.97%, respectively, emphasizing their critical role in selecting sustainable materials for EV interiors. Conversely, comfort (C) and aesthetic appeal (AA) had lower weights of 0.86% and 0.94%, respectively, signifying their relatively lesser but still relevant impact on decision-making.

The application of the Fuzzy-TOPSIS method facilitated the ranking of material alternatives based on their proximity to an ideal solution. As detailed in Table 13, polyethylene terephthalate (PET) emerged as the most suitable material, achieving a relative closeness coefficient (RCC) of 98.36%. This high-ranking underscore PET's strong performance across key criteria, particularly recyclability, durability, and a low carbon footprint. In contrast, bamboo fiber composite received the lowest RCC at 7.93%, reflecting its inadequacies, especially concerning energy requirements and manufacturing complexity. These findings highlight the effectiveness of the integrated

Fuzzy-Entropy and Fuzzy-TOPSIS framework in managing the complexities associated with sustainable material selection. The robustness of this approach was further validated through sensitivity analysis, which confirmed the stability of the ranking outcomes despite variations in criteria weights. Moreover, when compared against six standalone MCDM models in Table 14, the Fuzzy-Entropy-TOPSIS model demonstrated superior performance in capturing the relative significance of evaluation criteria and providing a clear and justified material ranking. The consistent identification of PET as the top-ranked material across multiple models reinforces the reliability of the findings and suggests PET as a highly viable option for enhancing EV interior sustainability.

Beyond the numerical outcomes, PET was identified as the top alternative because it demonstrated an exceptional balance across environmental, performance, and economic criteria. Environmentally, PET is derived from recycled post-consumer products, significantly reducing the need for virgin raw materials and lowering its overall carbon footprint. Its high recyclability ensures alignment with circular economy principles, and its production consumes less energy compared to producing virgin plastics. From a performance standpoint, PET offers excellent durability, strength, and resistance to UV radiation, moisture, and chemicals, making it highly suitable for demanding automotive interior conditions. Furthermore, it provides comfort and aesthetic flexibility, supporting high-quality finishes required for EV interiors. Economically, PET is a cost-effective material as it benefits from established recycling streams, making it cheaper than many bio-based polymers and easier to process with existing manufacturing infrastructure, thus reducing complexity in manufacturing. This combination of sustainability, robust mechanical properties, consumer appeal, and production feasibility contributed to its highest relative closeness coefficient (RCC) value in the Fuzzy-Entropy-TOPSIS model.

In summary, the application of Fuzzy MCDM techniques in this study provided a systematic and nuanced evaluation of eco-friendly materials for EV interiors. Identifying PET as the optimal material offers valuable insights for automotive manufacturers striving to enhance the sustainability of their products. The proposed methodological approach can be extended to similar decision-making problems in other fields, supporting broader initiatives in environmental sustainability and performance-driven material selection.

3.1.1 Comparative analysis with other MCDM models

The alternative ranking obtained from fuzzy-entropy-TOPSIS hybrid model was compared in Table 14 with six other solo MCDM methods namely, ARAS, COPRAS, MOORA, MULTIMOORA, WSM, and WPM. To validate the robustness of the proposed Fuzzy-Entropy-TOPSIS framework, the ranking outcomes were independently reproduced by the authors using six additional standalone MCDM methods namely, ARAS, COPRAS, MOORA, MULTIMOORA, WSM, and WPM. All seven methods, including the primary TOPSIS approach, were implemented by the authors using the same decision matrix, and criteria weights derived earlier in the study using Entropy. The ranking comparisons are also illustrated graphically shown in Fig. 2.

To validate the reliability and robustness of the proposed Fuzzy-Entropy-TOPSIS framework, the results were compared with six additional well-established MCDM methods: ARAS, COPRAS, MOORA, MULTIMOORA, WSM, and WPM. These methods were selected because they represent a broad spectrum of classical and modern decision-making approaches commonly used in material selection, engineering design, and sustainability evaluation. ARAS and COPRAS are both utility-based methods that consider both beneficial and non-beneficial criteria, providing interpretable rankings based on performance scores. MOORA and MULTIMOORA are widely applied in engineering and manufacturing decisions due to their computational simplicity and high discriminatory power. WSM and WPM are foundational aggregation-based models that serve as baseline comparators in MCDM research. By including these six diverse methods, the study ensures a comprehensive evaluation of ranking consistency and enhances confidence in the robustness of the proposed hybrid fuzzy framework.

Table 14. Comparisons with other MCDM models *(Source: Author’s own elaboration)*

Alternatives	TOPSIS	ARAS	COPRAS	MOORA	MULTIMOORA	WSM	WPM
BFC	4	4	4	4	4	4	4
PET	1	1	1	1	1	1	1
HFC	3	2	2	2	2	2	2
PLA	2	3	3	3	3	3	3

Table 14 clearly shows that PET consistently ranked first (1st) and BFC ranked lowest (4th) across all applied methods, including TOPSIS, ARAS, COPRAS, MOORA, MULTIMOORA, WSM, and WPM. PET’s top ranking across all methods highlights its superiority in balancing various criteria such as recyclability, durability, strength, and a lower carbon footprint. This consistent ranking indicates a strong consensus among the MCDM methods regarding PET’s suitability for EV interiors. Likewise, the uniform ranking of BFC as the lowest across all methods suggests a general agreement on its inferior performance, likely due to higher complexity in manufacturing and energy requirements. PLA ranked 2nd in TOPSIS and 3rd in ARAS, COPRAS, MOORA, MULTIMOORA, WSM, and WPM, whereas HFC ranked 3rd in TOPSIS and 2nd in the remaining methods. The variation in ranking suggests that PLA performed better under the specific evaluation framework of TOPSIS, particularly in criteria related to strength and comfort. On the other hand, HFC’s higher ranking in methods other than TOPSIS suggests it demonstrated a well-balanced performance across most criteria, though slightly lower than PET. The divergence in rankings may be attributed to differences in sensitivity to criteria weights and separation measures used by TOPSIS compared to the other methods.

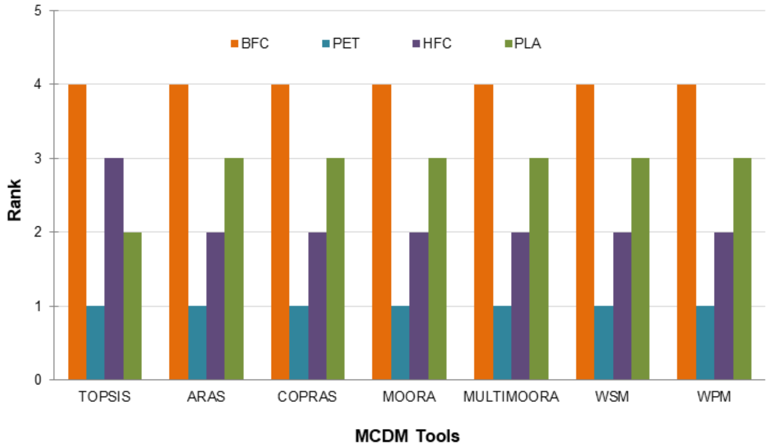

Fig. 2. Ranking comparisons *(Source: Author's own elaboration)*

The consistent rankings of BFC and PET across all methods confirm the reliability of MCDM techniques in decision-making. The minor variability in HFC and PLA rankings suggests their performance is more sensitive to specific criteria and weights, emphasizing the need for careful weight selection. PET's stability as the top material, even under sensitivity analysis, reinforces its suitability for eco-friendly EV interiors. The combined Fuzzy-Entropy and Fuzzy-TOPSIS approach effectively incorporated uncertainty and subjective judgment, with entropy determining criteria weights and TOPSIS ranking alternatives. Comparing Fuzzy-Entropy-TOPSIS with six other MCDM methods confirms its robustness in material selection. PET's consistent top ranking highlights its eco-friendly potential, contributing to sustainability in the automotive industry. Conversely, BFC's lower ranking across all methods identifies its limitations, guiding future research in sustainable material development.

3.1.2 Sensitivity analysis

This section delves into the sensitivity analysis of the Fuzzy-Entropy-TOPSIS model used to rank eco-friendly materials for EV interiors. The objective is to test the robustness of the ranking results against changes in the weight of the most important criterion, complexity in manufacturing, which had the highest weightage in the general set [14,24]. By varying the weight of CM within the range [0, 0.5399] at an interval of 0.05 and redistributing the remaining weights proportionally, 13 new sets of criteria weights were generated in Table 15. These new weights were applied to the problem, and the resulting rankings were analyzed to observe the stability of the method depicted in Fig. 3. The max value (w_j^*) upto which the 'CM' weight can be increased are determined using Eq. (16) [32]. In Eq. (16), 'w_j^{max}' and 'w_j^{min}' represents the criteria with the maximum and minimum weightage value. In the present case, 'w_j^{max}' indicates 'complexity in manufacturing (CM)' with the maximum weight of '0.4715' and 'w_j^{min}' indicates 'comfort (C)' with the minimum weight of '0.0086'. Similarly, 'n=9' represents the number of criteria considered for the present analysis.

$$w_j^* = [w_j^{max} + (n-1) \times w_j^{min}] \quad (16)$$

Table 15. Generating new sets of criteria weights *(Source: Author's own elaboration)*

	R	D	S	C	AA	CF	P	ER	CM
General set	0.0511	0.0813	0.0499	0.0086	0.0094	0.0155	0.2697	0.0431	0.4715
Set 1	0.1100	0.1402	0.1089	0.0675	0.0683	0.0744	0.3287	0.1020	0
Set 2	0.1037	0.1340	0.1026	0.0612	0.0620	0.0682	0.3224	0.0958	0.05
Set 3	0.0975	0.1277	0.0964	0.0550	0.0558	0.0619	0.3162	0.0895	0.1
Set 4	0.0912	0.1215	0.0901	0.0487	0.0495	0.0557	0.3099	0.0833	0.15
Set 5	0.0850	0.1152	0.0839	0.0425	0.0433	0.0494	0.3037	0.0770	0.2
Set 6	0.0787	0.1090	0.0776	0.0362	0.0370	0.0432	0.2974	0.0708	0.25
Set 7	0.0725	0.1027	0.0714	0.0300	0.0308	0.0369	0.2912	0.0645	0.3
Set 8	0.0662	0.0965	0.0651	0.0237	0.0245	0.0307	0.2849	0.0583	0.35
Set 9	0.0600	0.0902	0.0589	0.0175	0.0183	0.0244	0.2787	0.0520	0.4
Set 10	0.0537	0.0840	0.0526	0.0112	0.0120	0.0182	0.2724	0.0458	0.45
Set 11	0.0511	0.0813	0.0499	0.0086	0.0094	0.0155	0.2697	0.0431	0.4715
Set 12	0.0475	0.0777	0.0464	0.0050	0.0058	0.0119	0.2662	0.0395	0.5
Set 13	0.0425	0.0727	0.0414	0.0000	0.0008	0.0069	0.2612	0.0346	0.5399

Fig. 3 illustrates PET's consistent top ranking across all 13 sets, confirming its stability and robustness as the best material for eco-friendly EV interiors. This resilience under varying weight conditions highlights PET's superior performance across multiple criteria. In contrast, BFC initially ranked 3rd until Set 4 but then remained at the 4th position, affirming its status as the least favorable material. This consistency indicates that BFC's performance does not improve significantly, even with weight adjustments. HFC and PLA exhibited ranking shifts, with HFC holding 2nd place until Set 8 before dropping to 3rd, while PLA started in 4th, moved to 3rd after Set 4, and secured 2nd place from Set 9 onward. These shifts suggest that as the weight of CM increased, HFC's ranking declined while PLA's improved. The sensitivity analysis reinforces the reliability of the Fuzzy-Entropy-TOPSIS method, demonstrating its robustness in ranking materials consistently. PET's stable top position and BFC's persistent lowest ranking confirm the method's reliability, while the shifts in HFC and PLA emphasize the impact of criteria weighting. These findings highlight the importance of selecting appropriate criteria to ensure sustainable material choices for EV interiors.

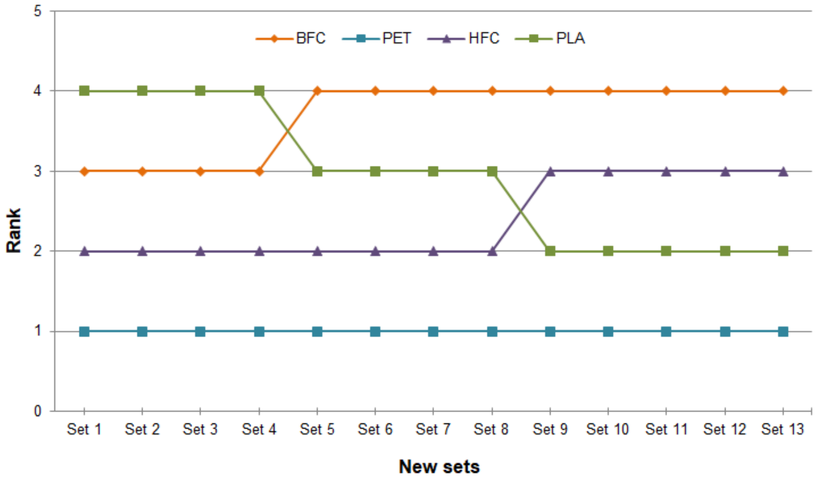

Fig. 3. Ranking variations *(Source: Author's own elaboration)*

The data used in this study were collected through a structured and systematic process involving three expert groups composed of professionals specializing in environmental science, automotive design, and decision sciences. To ensure reliability, each expert team independently evaluated the performance of material alternatives against the selected criteria using predefined linguistic variables, which were later converted into triangular fuzzy numbers based on a standardized fuzzy scale (as shown in Table 5). The aggregation of three independent expert opinions helped to minimize individual bias and enhance the consistency of the decision matrix. For validity, the selected criteria and material alternatives were chosen based on an extensive literature review, ensuring that the evaluation framework was aligned with current academic and industrial practices related to eco-friendly material selection for EV interiors. Furthermore, a sensitivity analysis was conducted by varying the weight of the most influential criterion, which demonstrated that the ranking of the best alternative (PET) remained stable under different scenarios, further supporting the robustness and validity of the findings. To additionally strengthen the validity, the final material rankings obtained through the proposed Fuzzy-Entropy-TOPSIS method were compared against six standalone MCDM methods (ARAS, COPRAS, MOORA, MULTIMOORA, WSM, and WPM), showing consistent results across all models. This triangulation across expert opinions, sensitivity testing, and comparative analysis ensures that the data used in the study are both reliable and valid for the decision-making process.

3.1.3 Practical implications

The application of the fuzzy MCDM model for selecting eco-friendly materials in EV interiors offers significant benefits to the automotive industry. The hybrid Fuzzy-Entropy-TOPSIS approach provides a structured framework for evaluating materials based on multiple conflicting criteria, ensuring an optimal balance of sustainability, cost, durability, and aesthetics. By identifying eco-friendly materials, the model supports sustainability goals and regulatory compliance while reducing the industry's carbon footprint. It effectively handles trade-offs between cost, environmental impact, and performance through subjective judgment and uncertainty quantification. Additionally, its structured and transparent nature enhances stakeholder communication, facilitating smoother implementation. Manufacturers adopting this approach gain a competitive edge by appealing to environmentally conscious consumers, while its customizable framework allows broader applications beyond EV interiors. The model streamlines material selection, improving cost-effectiveness, efficiency, and decision-making reliability through data-driven insights. As the automotive sector continues to prioritize sustainability, this approach will be crucial in guiding material selection that meets performance, cost, and environmental standards.

3.1.4 Limitations

The Fuzzy-Entropy-TOPSIS model provides valuable insights into selecting eco-friendly EV interior materials but has limitations. Evaluating only four alternatives ensures manageability but may overlook other viable options.

Expanding the selection could enhance comprehensiveness but adds complexity. The entropy-based criteria weights remain static, whereas real-world factors like technological advancements and market shifts can alter their importance. Fuzzy logic introduces subjectivity in defining linguistic variables, leading to inconsistencies in expert assessments. This can affect ranking reliability as interpretations vary. Additionally, the model is computationally intensive, making it less practical for smaller firms requiring quick decisions. Its complexity also demands expertise, limiting accessibility. The accuracy of rankings depends on high-quality, unbiased data. Any inconsistencies can impact results, making data reliability a crucial challenge. While the model offers a structured decision-making framework, recognizing its limitations in alternative scope, weight flexibility, subjectivity, complexity, and data sensitivity is essential for refining its applicability.

4 Conclusions

The research demonstrates the effectiveness of the Fuzzy-Entropy-TOPSIS hybrid MCDM model in selecting materials under multiple conflicting criteria. By integrating fuzzy logic, the model effectively handles uncertainty, while the entropy method ensures objective criteria weighting. The TOPSIS approach ranks alternatives efficiently, identifying PET as the most suitable material for EV interiors due to its balance between sustainability and performance, whereas BFC ranks the lowest. Sensitivity analysis and comparisons with other MCDM methods confirm the robustness of these findings.

Despite some limitations, the study offers a structured approach with practical implications for the automotive industry. Future research could broaden the evaluation to include a wider variety of eco-friendly materials, potentially uncovering superior alternatives for sustainable applications. Incorporating qualitative factors such as consumer preferences and market trends through methods like AHP or Delphi would offer a more holistic assessment. Extending the application of the Fuzzy-Entropy-TOPSIS model to other industries, such as consumer electronics and construction, could demonstrate its versatility and robustness. Additionally, real-world implementation and field testing of selected materials in electric vehicle (EV) interiors would provide practical validation and deeper insights into sustainability challenges.

While the current study focused on a structured scientific evaluation, practical performance aspects—including thermal resistance, behavior under extreme environmental conditions, and long-term durability—were not directly addressed to maintain methodological consistency and ensure fair comparability of the selected alternatives based on standardized evaluation criteria. Future work will aim to integrate these critical factors, such as thermal, acoustic, and UV degradation performance under dynamic conditions, thereby enhancing the model’s industrial relevance and aiding automotive manufacturers in validating and adopting eco-friendly materials under real-world constraints.

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7 Conflict of interest statement

The authors don’t have any conflict of interest.

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9 Availability statement

All the data are included in the article.

10 Supplementary materials

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