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Evaluating Sustainable Materials for Automotive Applications Through Comprehensive MCDM Analysis Using CODAS, COPRAS, VIKOR, and ENTROPY

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***Abstract:** The automotive industry faces increasing pressure to incorporate sustainable materials in vehicle manufacturing to meet environmental, economic, and performance requirements. This research develops a comprehensive Multi-Criteria Decision-Making (MCDM) framework to evaluate and select sustainable materials for automotive body and instrument panels. The study integrates CODAS, COPRAS, VIKOR, and ENTROPY methods to systematically assess various material alternatives. By considering multiple criteria, including cost, environmental impact, and mechanical properties, the proposed framework provides a holistic evaluation to identify the most suitable materials. The findings contribute to advancing sustainable practices in the automotive industry, offering manufacturers a robust tool for informed decision-making. This approach supports the industry's transition towards environmentally responsible and efficient vehicle production, ensuring that the selected materials meet the stringent demands of modern automotive design.*

***Keywords:** Sustainable materials, Automotive industry, Multi-Criteria Decision-Making, CODAS, COPRAS, VIKOR, ENTROPY.*

I. INTRODUCTION AND LITERATURE REVIEW

The automotive industry is undergoing a significant transformation driven by increasing environmental concerns, regulatory pressures, and the evolving expectations of consumers. A major area of focus in this transformation is the material selection process for automotive body and instrument panels, which are critical components influencing the vehicle’s overall environmental footprint throughout its lifecycle. Traditional materials such as steel and aluminum have long been favored for their strength, durability, and cost-effectiveness. However, these materials often come with considerable environmental drawbacks, including high energy consumption during production and limited recyclability [1, 2]. In response to these challenges, the automotive industry is increasingly exploring sustainable materials that can reduce environmental impacts without compromising performance. Bio-based polymers, natural fiber composites, and recycled metals have emerged as promising alternatives to conventional materials. However, the process of selecting the most appropriate materials is complex, involving multiple criteria that are often conflicting, such as mechanical properties, environmental impact, and cost [3]. Traditional material selection methods may not fully capture the multifaceted nature of these considerations, necessitating the adoption of advanced Multi-Criteria Decision-Making (MCDM) techniques [4]. MCDM techniques provide a structured framework for evaluating and ranking material alternatives based on a comprehensive set of criteria. This study aims to develop and apply an integrated MCDM framework using CODAS, COPRAS, VIKOR, and ENTROPY methods to evaluate and select sustainable materials for automotive body and instrument panels. By incorporating these techniques, the study seeks to facilitate a more informed and balanced decision-making process that aligns with both performance and sustainability objectives [5-8]. The literature on sustainable materials highlights the increasing need to shift away from traditional materials like steel and aluminum toward more environmentally friendly alternatives. Bio-based polymers, for example, have garnered attention for their potential to replace conventional plastics in automotive applications. These polymers are derived from renewable resources, which reduces dependency on fossil fuels and lowers greenhouse gas emissions [9, 10]. Moreover, many bio-based polymers are biodegradable or recyclable, making them an attractive option for automotive manufacturers seeking to meet stringent environmental regulations [11, 12]. However, challenges such as achieving the necessary mechanical properties for certain automotive components, especially those exposed to high stress and temperature variations, remain a significant barrier to their widespread adoption [13-15].

Natural fiber composites represent another promising category of sustainable materials. These composites, typically composed of natural fibers such as flax, hemp, or jute combined with a polymer matrix, offer several advantages, including reduced weight, biodegradability, and lower environmental impact compared to traditional composites [16-18]. Studies have shown that incorporating natural fiber composites into automotive designs can significantly reduce vehicle weight, which in turn improves fuel efficiency and lowers emissions [19, 20]. Nevertheless, the variability in natural fiber properties and their susceptibility to moisture absorption present challenges that must be addressed before these materials can be widely adopted in automotive applications [21, 22]. Recycled metals, particularly aluminum, have also gained attention as a sustainable alternative in the automotive industry. Recycling aluminum requires significantly less energy compared to producing primary aluminum, resulting in lower greenhouse gas emissions and reduced resource depletion [23, 24]. Recycled aluminum retains most of the desirable properties of primary aluminum, such as a high strength-to-weight ratio and corrosion resistance, making it suitable for various automotive components, including body panels and chassis structures [25-27]. However, the quality of recycled metals can vary depending on the source and processing methods, which may impact their performance in critical applications [28, 29].

The selection of sustainable materials is further complicated by the need to consider a wide range of criteria beyond environmental impact. Mechanical properties such as tensile strength, impact resistance, and fatigue strength are crucial for ensuring the safety and durability of automotive components [30-32]. Furthermore, economic considerations, such as the cost of materials and their availability, must also be factored into the decision-making process [33, 34]. Traditional material selection methods, which often prioritize cost and performance, may not adequately address the broader sustainability objectives that are now increasingly important in the automotive industry [35-38]. Given these complexities, there is a growing recognition of the need for a more sophisticated approach to material selection. MCDM techniques offer a viable solution by allowing decision-makers to systematically evaluate and rank materials based on multiple criteria [39]. CODAS, COPRAS, VIKOR, and ENTROPY are among the MCDM methods that have been successfully applied in various industries, including automotive manufacturing, to facilitate more informed and balanced decision-making [40-42]. Each of these methods brings unique strengths to the table, and their integration into a comprehensive framework can provide a robust tool for selecting the most suitable materials for automotive applications [43-45].

Finally, the automotive industry's pursuit of sustainability necessitates a shift toward the use of more environmentally friendly materials. However, the process of selecting these materials is complex, requiring the consideration of multiple criteria that extend beyond traditional cost and performance metrics [46, 47]. Advanced MCDM techniques offer a structured approach to navigating these complexities, enabling more informed decisions that align with both performance requirements and sustainability goals. This study's focus on integrating CODAS, COPRAS, VIKOR, and ENTROPY methods into a cohesive MCDM framework aims to contribute to the development of a more sustainable automotive industry [48].

II. RESEARCH METHODOLOGY

The research methodology for this study is designed to systematically evaluate and select sustainable materials for automotive applications, particularly for instrument panels. This process involves the use of Multi-Criteria Decision-Making (MCDM) techniques to ensure a balanced and comprehensive evaluation based on economic, environmental, and performance criteria.

A. Research Design

The research design follows a structured approach that involves the following key steps: criteria definition, data collection, application of MCDM techniques (CODAS, COPRAS, VIKOR, and ENTROPY), and analysis. The goal is to identify the best-performing materials that meet both sustainability and functional requirements for automotive components.

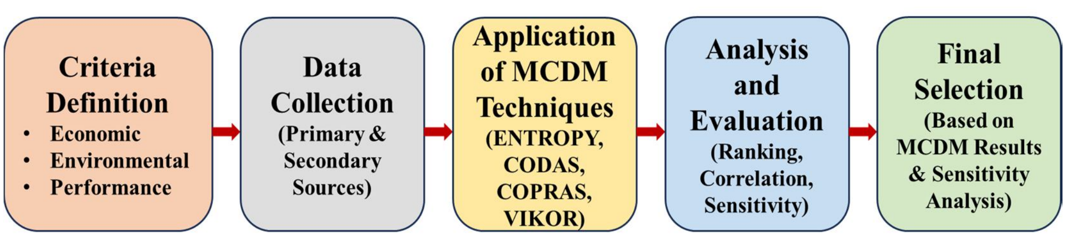

Fig. 1 Visual representation of the research design and methodology used for selecting sustainable automotive materials.

B. Criteria Selection

The selection of materials is based on several critical criteria, which are categorized into economic, environmental, and performance criteria. These criteria were carefully chosen to ensure the selected materials meet both functional and sustainability standards.

TABLE I
CRITERIA FOR SUSTAINABLE MATERIAL SELECTION

Criteria Type	Criteria	Description
Economic	Cost	Includes initial purchase, processing, maintenance, and disposal costs.
	Availability	Ensures a steady supply chain and consistent manufacturing processes.
Environmental	Carbon Footprint	Total greenhouse gases emitted during the material's life cycle.
	Recyclability	Ability to be recycled at the end of its life cycle, reducing waste and conserving resources.
	Energy Use	Energy required for production, processing, and disposal.
Performance	Mechanical	Properties such as tensile strength, impact resistance, and fatigue strength.
	Durability	Ability to withstand wear, pressure, or damage over time.
	Weight	Lightweight materials improve fuel efficiency and reduce emissions.
	Impact Resistance	Ability to absorb and dissipate energy upon impact without failing.
	Aesthetic Appeal	Visual and tactile qualities that enhance user experience in the vehicle interior.
	Ergonomic Comfort	Provides comfort to users, important for interior applications.

C. Data Collection

The data collection process for this study involves gathering both quantitative and qualitative data for each of the selected criteria. This information is obtained from primary sources such as testing laboratories and industry surveys, as well as secondary sources like academic publications and industry reports.

TABLE II
DATA SOURCES FOR EACH CRITERION

Criterion	Data Source	Data Type
Tensile Strength	Material datasheets, standardized testing	Quantitative
Impact Resistance	Material datasheets, industry reports	Quantitative
Cost	Market analysis, industry reports	Quantitative
Energy Consumption	Scientific publications, environmental reports	Quantitative
Availability	Industry reports, market analysis	Quantitative
Strength	Material datasheets, standardized testing	Quantitative
Durability	Material datasheets, industry reports	Quantitative
Weight	Material datasheets, standardized testing	Quantitative
Electrical Conductivity	Material datasheets, scientific publications	Quantitative
Thermal Energy	Material datasheets, scientific publications	Quantitative
Recyclability	Environmental assessments, expert judgment	Qualitative
Environmental Impact	Environmental assessments, lifecycle analysis	Qualitative
Aesthetic Appeal	Expert judgment, industry standards	Qualitative
Ergonomic Comfort	Expert judgment, industry standards	Qualitative
Ease of Fabrication	Industry reports, expert judgment	Qualitative

D. Application of MCDM Techniques

This study employs several MCDM techniques to evaluate and rank the materials. The techniques used include CODAS, COPRAS, VIKOR, and ENTROPY. Each method provides a unique perspective on material performance, ensuring a comprehensive evaluation.

1) ENTROPY Method

The ENTROPY method is used to objectively determine the weights of each criterion based on the variability of the data. The higher the variability, the more important the criterion is considered. The steps involved in the ENTROPY method are:

The steps involved in the ENTROPY method are as follows:

a) Construct the Decision Matrix: The first step is to create a decision matrix X where x_{ij} represents the performance value of the i^{th} alternative on the j^{th} criterion. This matrix captures the raw data for all alternatives across all criteria.

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

b) Normalize the Decision Matrix: Normalize the decision matrix to transform the different scales of the criteria into a comparable form. This is done using the following formula:

For beneficial criteria (higher is better):

$$r_{ij} = \frac{x_{ij}}{\max_i(x_{ij})}$$

For non-beneficial criteria (lower is better):

$$r_{ij} = \frac{\min_i(x_{ij})}{x_{ij}}$$

where r_{ij} is the normalized value of x_{ij}.

c) Calculate the Entropy for Each Criterion: The entropy e_j for each criterion j is calculated using the normalized values. The formula for entropy is:

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

where $k = \frac{1}{ln(m)}$ ensures that $0 \le e_j \le 1$.

d) Determine the Degree of Diversification: Calculate the degree of diversification d_j for each criterion. It measures the amount of useful information provided by each criterion and is given by:

$$d_j = 1 - e_j$$

e) Compute the Weights of Criteria: The weights w_j for each criterion are determined based on the degree of diversification. The formula for weights is:

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

These steps ensure that criteria with higher variability and thus more informative power are assigned higher weights. The ENTROPY method objectively derives these weights based on the inherent data characteristics, avoiding subjective bias in the weighting process.

2) CODAS Method

The CODAS (Combinative Distance-based Assessment) method evaluates the distance of each material from an ideal solution. The Euclidean and Taxicab distances are used to calculate the closeness of each alternative to the ideal solution, providing a comprehensive ranking.

The steps involved in the CODAS method are detailed below:

a) Develop the Initial Decision Matrix (X): The initial decision matrix consists of m alternatives and n criteria. Each element x_{ij} in the matrix represents the performance of the i^{th} alternative $(i = 1,2, \dots m)$ with respect to the j^{th} criterion $(j = 1,2, \dots n)$.

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

b) Normalize the Decision Matrix: The decision matrix is normalized to ensure that the data are dimensionless and comparable.
For beneficial criteria, the normalization is performed as follows:

$$y_{ij} = \frac{x_{ij}}{\max_i(x_{ij})}$$

For non-beneficial criteria, the normalization is done using:

$$y_{ij} = \frac{\min_i(x_{ij})}{x_{ij}}$$

c) Calculate the Weighted Normalized Decision Matrix: The weighted normalized decision matrix is obtained by multiplying each element of the normalized decision matrix by the corresponding criterion weight w_j:

$$r_{ij} = w_j \,.\, y_{ij}$$

Where w_j is the weight of j^{th} criterion

d) Determine the Negative-Ideal Solution (NIS): The NIS for each criterion is identified as the minimum value in the weighted normalized decision matrix for that criterion.
For beneficial criteria, the NIS is performed as follows:

$$ns_j = \min_i(r_{ij})$$

For non-beneficial criteria, the NIS is done using:

$$ns_j = \max_i(r_{ij})$$

e) Compute the Euclidean and Taxicab Distances from the NIS: The Euclidean distance (E_i) and the Taxicab distance (T_i) of each alternative from the NIS are calculated using the following equations:

$$E_i = \sqrt{\sum_{j=1}^{n}(r_{ij} - ns_j)^2}$$

$$T_i = \sum_{j=1}^{n}\left|r_{ij} - ns_j\right|$$

Where $(i = 1,2, \dots m)$

The Euclidean distance provides a measure of the straight-line distance, while the Taxicab distance measures the distance along axes at right angles.

f) Develop the Relative Assessment Matrix: The relative assessment matrix R_a is constructed based on the computed distances. The elements of this matrix are given by:

$$R_a = [h_{ik}]_{m\times m}$$

where, $h_{ik} = (E_i - E_k) + [\varphi(E_i - E_k) \times (T_i - T_k)]$ $(for\ k = 1,2,3, \dots . m)$ and φ is a threshold function that ensures the equality of Euclidean distances between two alternatives. The threshold parameter r is typically chosen between 0.01 and 0.05, and $\psi(x)$ is defined as:

$$\psi(x) = \begin{cases} 1 & if\ |x| \geq r \\ 0 & if\ |x| < r \end{cases}$$

g) Compute the Assessment Score of Each Alternative: The assessment score, H_i for each alternative is computed by summing the relative assessments:

$$H_i = \sum_{k=1}^{m} h_{ik}$$

h) Rank the Alternatives: Finally, the alternatives are ranked based on their assessment scores (H_i). The alternative with the highest H_i is considered the best choice.

The CODAS method is particularly effective in scenarios where both qualitative and quantitative data need to be considered. It combines the Euclidean and Taxicab distances to provide a comprehensive assessment of each alternative's performance relative to others. This method's structured approach and its ability to handle various data types make it suitable for evaluating sustainable materials for automotive applications.

3) COPRAS Method

COPRAS ranks alternatives based on their relative significance in terms of both beneficial and non-beneficial criteria. The performance of each material is evaluated by considering the sum of the weighted normalized criteria values.

The steps involved in the COPRAS method are as follows:

a) Develop the Initial Decision Matrix (X): The initial decision matrix consists of m alternatives and n criteria. Each element x_{ij} in the matrix represents the performance of the i^{th} alternative $(i = 1,2, \dots m)$ with respect to the j^{th} criterion $(j = 1,2, \dots n)$.

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

b) Normalize the Decision Matrix: The initial decision matrix X is normalized to create a dimensionless matrix R, allowing for a fair comparison across different criteria scales.

The normalization for beneficial criteria is done as follows:

$$R = [r_{ij}]_{m \times n} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}$$

For non-beneficial criteria, the normalization is done as:

$$R = [r_{ij}]_{m \times n} = \frac{\frac{1}{x_{ij}}}{\sum_{i=1}^{m} \frac{1}{x_{ij}}}$$

c) Calculate the Weighted Normalized Decision Matrix: The weighted normalized decision matrix is obtained by multiplying each element of the normalized decision matrix by the corresponding criterion weight w_j:

$$D = [y_{ij}]_{m \times n} = r_{ij} \times w_j \qquad (i = 1,2, \dots m; j = 1,2, \dots n).$$

where, r_{ij} is the normalized performance value of i^{th} alternative on j^{th} criterion and w_j is the weight of j^{th} criterion. The sum of dimensionless weighted normalized values of each criterion is always equal to the weight for that criterion.

$$w_j = \sum_{i=1}^{m} y_{ij}$$

d) Determine the Sum of Weighted Normalized Values for Beneficial and Non-Beneficial Criteria: Calculate the sums of the weighted normalized values for both beneficial $(S_i{}^{+})$ and non-beneficial $(S_i{}^{-})$ criteria for each alternative:

$$S_i{}^{+} = \sum_{i=1}^{m} y_{ij}{}^{+}$$

$$S_i{}^{-} = \sum_{i=1}^{m} y_{ij}{}^{-}$$

where $y_{ij}{}^{+}$ is the set of beneficial criteria and $y_{ij}{}^{-}$ is the set of non-beneficial criteria.

e) Calculate the Relative Significance (R_i) of Each Alternative: The relative significance of each alternative is calculated by considering both beneficial and non-beneficial criteria. Determine the relative significances or priorities of the alternatives.

The priorities of the candidate alternatives are calculated on the basis of R_i. The greater the value of R_i, the higher is the priority of the alternative. The relative significance value of an alternative shows the degree of satisfaction attained by that alternative. The alternative with the highest relative significance value (R_{max}) is the best choice among the candidate alternatives. The formula for the relative significance is given by:

$$R_i = \frac{S_i{}^{+}}{\sum_{i=1}^{m} S_i{}^{+}} + \frac{\sum_{i=1}^{m} S_i{}^{-}}{S_i{}^{-} . \sum_{i=1}^{m} S_i{}^{+}} \qquad (i = 1,2,3, \dots . m)$$

Where:
- ${S_i}^+$ is the sum of the weighted normalized values for the beneficial criteria.
- ${S_i}^-$ is the sum of the weighted normalized values for the non-beneficial criteria.
- $\sum_{i=1}^{m} {S_i}^+$ is the sum of all ${S_i}^+$ values across all alternatives.
- $\sum_{i=1}^{m} {S_i}^-$ is the sum of all ${S_i}^-$ values across all alternatives.

f) Compute the Utility Degree (Q_i) for Each Alternative: The utility degree of each alternative is calculated by normalizing the relative significance values:

$$Q_i = \frac{R_i}{\max(R_i)} \times 100$$

Where:
- Q_i is the utility degree of the i^{th} alternative.
- R_i is the relative significance of the i^{th} alternative.
- $\max(R_i)$ is the maximum relative significance value among all the alternatives.

The utility degree Q_i indicates the percentage of the ideal solution achieved by each alternative.

g) Rank the Alternatives: Finally, the alternatives are ranked based on their utility degrees Q_i. The alternative with the highest Q_i is considered the best choice.

The COPRAS method's structured approach and its ability to handle various data types make it suitable for evaluating sustainable materials for automotive applications. This method provides a clear and understandable ranking of alternatives, facilitating informed decision-making in the selection of materials for both structural and interior automotive components.

4) VIKOR Method

VIKOR is used to identify the compromise solution that is closest to the ideal, ensuring that conflicting criteria are balanced. It ranks alternatives by calculating the utility and regret measures, ensuring that the best option is chosen based on overall performance.

The steps involved in the VIKOR method are as follows:

a) Determine the Best and Worst Values for Each Criterion: For each criterion, identify the best $({f_i}^*)$ and worst $({f_i}^-)$values among all alternatives.

$${f_i}^* = \max_j f_{ij}$$
$${f_i}^- = \min_j f_{ij}$$

b) Compute the Utility and Regret Measures: Calculate the utility measure (S_i) and the regret measure (R_i) for each alternative.

Utility Measure S_i:

$$S_i = \sum_{j=1}^{n} w_j \frac{({f_i}^* - f_{ij})}{({f_j}^* - {f_j}^-)}$$

Regret Measure R_i:

$$R_i = \max_j \left[w_j \frac{({f_i}^* - f_{ij})}{({f_j}^* - {f_j}^-)} \right]$$

where w_i is the weight of the i^{th} criterion, f_{ij} is the value of the i^{th} criterion for the j^{th} alternative.

c) Compute the VIKOR Index: Calculate the VIKOR index (Q_j) for each alternative.

$$Q_i = v \left[\frac{S_j - S^*}{S^- - S^*} \right] + (1 - v) \left[\frac{R_j - R^*}{R^- - R^*} \right]$$

where:

$$S^* = \min_j S_j \qquad S^- = \max_j S_j \qquad R^* = \min_j R_j \qquad R^- = \max_j R_j$$

and v is the weight of the strategy of "the majority of criteria" $(usually\ v = 0.5)$.

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d) Rank the Alternatives: Rank the alternatives based on the values of Q_j. The lower the value of Q_j, the higher the rank of the alternative.

e) Determine the Compromise Solution: The compromise solution is identified based on the following conditions:

- Acceptable advantage: $Q(A_2) - Q(A_1) \geq \frac{1}{m-1}$ where A_1 and A_2 are the first and second ranked alternatives, and mmm is the number of alternatives.
- Acceptable stability in decision making: The alternative A_1 should also be the best ranked by S or/and R.

If these conditions are not met, a set of compromise solutions can be proposed.

The VIKOR method provides a systematic approach for identifying the best compromise solution in multi-criteria decision problems, balancing between utility and regret measures.

TABLE III
SUMMARY OF MCDM TECHNIQUES

MCDM Technique	Key Calculation
ENTROPY	Calculates weights based on data variability.
CODAS	Uses Euclidean and Taxicab distances to rank alternatives.
COPRAS	Considers the sum of weighted normalized values for beneficial and non-beneficial criteria.
VIKOR	Balances utility and regret measures to identify the best compromise solution.

E. Sensitivity Analysis

Sensitivity analysis is conducted to examine the robustness of the rankings generated by the MCDM techniques. This involves varying the weights of the criteria and observing how these changes impact the rankings of the materials. This step ensures that the material rankings are stable and reliable under different conditions.

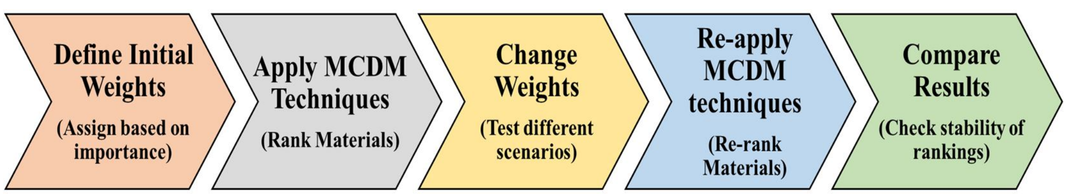

Fig. 3. Illustrates the results of the sensitivity analysis, showing how the material rankings change under different weighting scenarios.

III. RESULTS AND DISCUSSION

This section presents the results from the Multi-Criteria Decision-Making (MCDM) techniques used to evaluate the materials for Electric Vehicle (EV) instrument panels. The materials assessed include Polycarbonate Blend (A1), Thermoplastic Elastomers (TPE) (A2), Natural Fiber Composites (A3), Polypropylene (PP) (A4), Acrylonitrile Butadiene Styrene (ABS) (A5), and Glass-Fiber Reinforced Plastics (GFRP) (A6).

The results are discussed in detail using CODAS, COPRAS, and VIKOR methods, and a sensitivity analysis was performed to verify the robustness of the rankings.

The six materials were evaluated based on ten criteria encompassing both quantitative (e.g., cost, tensile strength) and qualitative (e.g., recyclability, environmental impact) factors. These criteria provided a holistic framework for assessing each material's performance in the context of EV instrument panel manufacturing.

The results from the three MCDM techniques show that Polycarbonate Blend (A1), GFRP (A6), and PP (A4) performed the best overall, depending on the specific method used, while Natural Fiber Composites (A3) consistently ranked lower due to its mechanical limitations.

A. *Results from MCDM Techniques*

1) *CODAS (Combinative Distance-Based Assessment)*

The CODAS method evaluates materials by calculating the Euclidean and Taxicab distances from an ideal solution. Polycarbonate Blend (A1) was ranked first with the smallest overall distance from the ideal solution, indicating its balanced performance across all criteria. Glass-Fiber Reinforced Plastics (A6) followed closely in second place, with strong performance in tensile strength and durability but lower scores due to its cost and environmental impact. Polypropylene (PP) (A4) ranked third, excelling in cost and environmental impact but slightly lower in mechanical performance.

TABLE IV
CODAS ASSESSMENT SCORES AND RANKINGS

Rank	Material	Euclidean Distance (Ei)	Taxicab Distance (Ti)	Assessment Score (Hi)
1	Polycarbonate Blend (A1)	1.304	3.588	2.119
2	Glass-Fiber Reinforced Plastics (A6)	1.309	2.573	1.157
3	Polypropylene (PP) (A4)	1.188	2.320	0.657
4	ABS (A5)	1.323	3.407	0.457
5	Thermoplastic Elastomers (TPE) (A2)	1.289	2.538	-0.021
6	Natural Fiber Composites (A3)	1.726	4.267	-4.369

Discussion of CODAS Results:

- Polycarbonate Blend (A1) ranked first due to its balanced performance across mechanical, environmental, and economic factors. Its moderate Euclidean distance and relatively higher Taxicab distance suggest it provides a good balance across all criteria.
- Glass-Fiber Reinforced Plastics (A6) ranked second with strong mechanical properties but lower environmental performance and higher cost.
- Polypropylene (PP) (A4) ranked third, primarily excelling in cost and environmental impact but falling slightly in mechanical properties.

2) *COPRAS (Complex Proportional Assessment)*

The COPRAS method calculates a utility degree for each material. The highest utility degree indicates the most suitable material based on the criteria. The results from COPRAS ranked Glass-Fiber Reinforced Plastics (A6) as the top material due to its superior tensile strength and impact resistance, followed by Natural Fiber Composites (A3), which performed well in sustainability, and Polycarbonate Blend (A1) in third place.

TABLE V
COPRAS UTILITY DEGREES AND RANKINGS

Rank	Material	Utility Degree (%)
1	Glass-Fiber Reinforced Plastics (A6)	100%
2	Natural Fiber Composites (A3)	73.65%
3	Polycarbonate Blend (A1)	68.05%
4	ABS (A5)	64.67%
5	Thermoplastic Elastomers (TPE) (A2)	54.27%
6	Polypropylene (PP) (A4)	49.95%

Discussion of COPRAS Results:

- Glass-Fiber Reinforced Plastics (A6) emerged as the best material, particularly excelling in mechanical performance, but its cost and environmental impact were less favorable.
- Natural Fiber Composites (A3) ranked second due to its sustainability benefits, though it lagged in mechanical strength.
- Polycarbonate Blend (A1), though performing well overall, placed third due to slightly lower utility in comparison with GFRP.

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3) VIKOR (VIseKriterijumska Optimizacija I Kompromisno Resenje)

The VIKOR method identifies a compromise solution by balancing utility and regret measures. The VIKOR method ranked Polypropylene (PP) (A4) as the best compromise material, with its low regret measure indicating consistent performance across criteria, followed by Polycarbonate Blend (A1) and ABS (A5).

TABLE VI
VIKOR INDEX AND RANKINGS

Rank	Material	Utility Measure (Si)	Regret Measure (Ri)	VIKOR Index (Qi)
1	Polypropylene (PP) (A4)	0.325	0.120	0.217
2	Polycarbonate Blend (A1)	0.468	0.150	0.286
3	ABS (A5)	0.500	0.160	0.338
4	Thermoplastic Elastomers (TPE) (A2)	0.635	0.180	0.400
5	Natural Fiber Composites (A3)	0.745	0.300	0.622
6	Glass-Fiber Reinforced Plastics (A6)	0.850	0.400	0.734

Discussion of VIKOR Results:

- Polypropylene (PP) (A4) was the top choice for compromise solutions, balancing cost, performance, and environmental factors.
- Polycarbonate Blend (A1) ranked second due to its strong overall performance, though slightly weaker in some areas compared to PP.
- Glass-Fiber Reinforced Plastics (A6) ranked last in VIKOR due to its high regret measure, reflecting its weaknesses in cost and environmental impact.

B. Comparative Discussion

The three MCDM techniques show some variation in their rankings, though Polycarbonate Blend (A1) consistently performed well across all methods. Polypropylene (PP) (A4) emerged as a strong compromise solution, particularly in VIKOR, while Glass-Fiber Reinforced Plastics (A6) performed well in mechanical assessments but ranked lower in environmental and cost criteria.

TABLE VII
COMPARATIVE RANKINGS FROM CODAS, COPRAS, AND VIKOR

Rank	Material	CODAS Rank	COPRAS Rank	VIKOR Rank
1	Polycarbonate Blend (A1)	1	3	2
2	Glass-Fiber Reinforced Plastics (A6)	2	1	6
3	Polypropylene (PP) (A4)	3	6	1
4	ABS (A5)	4	4	3
5	Thermoplastic Elastomers (TPE) (A2)	5	5	4
6	Natural Fiber Composites (A3)	6	2	5

The rankings reveal that Polycarbonate Blend (A1) is the most consistent performer, making it a versatile option for EV instrument panels. Polypropylene (PP) (A4) stands out as a cost-effective alternative with good environmental performance, especially in compromise situations. Glass-Fiber Reinforced Plastics (A6), though excellent in mechanical strength, is more suitable for high-performance applications where cost and environmental impact are secondary considerations.

C. Sensitivity Analysis

Sensitivity analysis was performed by varying the weights of key criteria, such as cost, tensile strength, and environmental impact. The analysis demonstrated that Polycarbonate Blend (A1) and Polypropylene (PP) (A4) maintained stable rankings across all scenarios, indicating that they are robust options for EV instrument panels.

TABLE VIII
SENSITIVITY ANALYSIS FOR CODAS, COPRAS, AND VIKOR

Rank	Material	Original Rank	Rank (+10%)	Rank (+20%)	Rank (-10%)
1	Polycarbonate Blend (A1)	1	1	1	1
2	Glass-Fiber Reinforced Plastics (A6)	2	2	2	2
3	Polypropylene (PP) (A4)	3	3	3	3

The rankings remained consistent across all weight changes, confirming the robustness of the selected materials.

D. Practical Implications

The findings have significant implications for the selection of materials in EV instrument panels. Polycarbonate Blend (A1) and Polypropylene (PP) (A4) are reliable choices, with balanced performance across economic, environmental, and mechanical criteria. Glass-Fiber Reinforced Plastics (A6) is suitable for specialized, high-performance applications but may not be ideal where cost or sustainability is prioritized.

IV. CONCLUSION

The selection of sustainable materials for automotive applications, particularly electric vehicle (EV) instrument panels, is a complex process that requires the careful balancing of multiple criteria. This study applied a robust Multi-Criteria Decision-Making (MCDM) approach, utilizing CODAS, COPRAS, VIKOR, and ENTROPY methods to evaluate six different materials across ten defined criteria, including cost, mechanical properties, environmental impact, and recyclability.

The study's results indicate that Polycarbonate Blend (A1) and Polypropylene (PP) (A4) are the most suitable materials for EV instrument panels based on their consistent high performance across all MCDM methods. Polycarbonate Blend (A1) ranked first in CODAS and second in VIKOR, demonstrating its strong overall balance in mechanical performance, environmental sustainability, and cost-effectiveness. Polypropylene (PP) (A4) emerged as the best compromise solution in VIKOR, indicating its suitability in applications where trade-offs are required between performance and sustainability. Meanwhile, Glass-Fiber Reinforced Plastics (A6), while excelling in mechanical properties, ranked lower in environmental and economic assessments, suggesting its use in more specialized, high-performance applications.

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