SSRG International Journal of Mechanical Engineering
ISSN: 2348-8360/ https://doi.org/10.14445/23488360/IJME-V12I12P104

Volume 12 Issue 12, 31-44, December 2025

Original Article

An Improved Multi-Criteria Method for Supplier Selection in Indian Automotive Manufacturing

Shankha Ghosh[1], Partha Sarathi Chakraborty[2], S. Nallusamy[3], M. Rajaram Narayanan[4]

[1,2,3]*Department of Adult, Continuing Education and Extension, Jadavpur University, Kolkata, India.*
[4]*Department of Computer Science and Engineering, Aalim Muhammed Salegh College of Engineering, Chennai, India.*

[1]*Corresponding Author : shankhaghosh007@gmail.com*

Received: 08 October 2025 Revised: 09 November 2025 Accepted: 11 December 2025 Published: 27 December 2025

Abstract - *In the medium-sized automotive sector, supplier selection is the most important factor in ensuring constant quality, cost management, and delivery performance. These sectors must deal with tight operational restrictions, interconnected criteria, and ambiguous information. As a result, choosing a supplier is a difficult choice. This article proposes an inventive strategy to address this issue over an integrated framework. 3.2. Fuzzy Analytic Hierarchy Process (FAHP) is used to calculate the criteria weights due to uncertainty, Fuzzy Decision-Making Trial and Evaluation Laboratory (FDEMATEL) is used to map cause and effect relationships, and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and Evaluation Based on Distance from Average Solution (EDAS) are used to assess supplier performance. Sensitivity analysis evaluates the stability of the results, whereas the Borda and Copeland Count methods combine the rankings. The FAHP score, the important factors are cost 0.128, quality 0.279, and delivery reliability 0.130. According to FDEMATEL, lower-weighted criteria indicate cause, and higher-weighted criteria indicate effect. TOPSIS and EDAS considered S1 and S2 to be the best performers, whereas S4 frequently scored lowest. These opinions were validated by Borda and Copeland aggregation. S1 and S2 maintained their top positions in every scenario, according to a sensitivity study with a weight variation of ±20%. Based on the results of this study, the integrated model offers a robust and clear base for the selection of suppliers.*

Keywords - *Supplier selection, MCDM, Rank Aggregation, Sensitivity analysis.*

1. Introduction

Supplier selection is one of the key concerns for medium-scale automotive manufacturers, which are driven by tight cost structures, unpredictable consumer demand, and increasing demands for quality, sustainability, and responsive production. Their ability to select and manage their suppliers, then, is just as important to their competitiveness as internal efficiency. A poor decision may result in delays, variable quality, increased operational hazards, and financial loss. A quality supplier base may, on the other hand, enable a company to increase product quality, eliminate waste, and respond quickly to changes in the marketplace. Thus, supplier selection is no longer a simple buying decision but a strategic decision [1-3]. Selecting the right supplier is difficult because the decision involves many criteria that often conflict with each other. Some of the major factors include quality, cost, delivery reliability, technical capability, financial stability, risk management, and environmental compliance [4-6]. These criteria involve both measurable information and subjective judgments from experts. In medium-scale automotive firms, the challenge becomes even sharper because managers often work with incomplete data and under uncertain conditions [7, 8]. It is for this reason that there has been an increased interest in fuzzy Multi-Criteria Decision-Making (MCDM) tools. They allow decision makers to express their opinions in more flexible terms and capture the uncertainty naturally present in human judgment [6, 9].

FAHP has been widely applied to determine the weights of selection criteria. FAHP handles linguistic judgments, reduces inconsistency, and improves the reliability of expert evaluations. It enables decision makers to compare criteria pairwise and express their views in fuzzy terms rather than exact numbers. The same applies in the automotive industry, where normally experts base their opinions on experience rather than exact data [10-12].

FDEMATEL adds another layer in highlighting cause-and-effect relationships among the criteria. Apart from simple weighting, the FDEMATEL method helps managers find out which factor drives which. For example, technical capability may drive quality, and a supplier relationship may drive delivery reliability. Mapping these relationships assists firms in focusing on the most influential factors. For medium-scale manufacturers with limited resources, this may give indications for better decision planning [13-15].

Once the criteria have been weighted, a ranking of suppliers' performances is required. To this end, various tools can be employed, including TOPSIS and EDAS. TOPSIS ranks alternatives based on their distance from both the ideal and negative-ideal solutions. This method is simple and intuitive, hence popular in industrial applications [16-18]. EDAS assesses alternatives according to their positive and negative distances to the average solution. It introduces another angle by considering the deviation from the mean rather than the distance from the ideal point [19-20]. The use of these two methods constitutes a firmer basis for confidence in the results of ranking. These secondary aggregation methods are useful in aggregating rankings produced by several MCDM tools. Among them is the Bodra method, which integrates various rankings into a single consolidated order. Copeland Count adds a voting-based aggregation method that compares alternatives pairwise and awards points based on their relative performance across methods [21-23]. These avert the bias arising when individual ranking methods are used. Integrating FAHP, FDEMATEL, TOPSIS, EDAS, Bodra, and Copeland Count provides a more robust and stable supplier selection framework.

In India and other developing regions, medium-scale automotive industries are tending towards hybrid decision models in order to manage supplier evaluation more effectively. Supply chains are increasingly complex, markets are competitive, and disruptions are more common. Though large companies have sophisticated systems and large procurement teams, medium-scale units require practical and reliable tools that guarantee decision-making with minimal resources. A combined fuzzy-based and ranking-aggregation approach fits these needs well [24, 25].

This article develops an integrated supplier selection framework for medium-scale automotive industries using FAHP for criteria weight calculation, FDEMATEL for identifying causal relationships, TOPSIS and EDAS for supplier ranking, and Bodra with Copeland Count for final consolidated ranking. Sensitivity analysis is provided to test the stability of the results for different conditions. In this respect, the proposed framework will provide a structured and thorough approach that will assist managers in making rational supplier selection decisions under uncertainty. It also contributes to the academic field by showing how different fuzzy and ranking tools can be combined for a more reliable evaluation system. The introduction sets the base for analyzing the performance of suppliers in a structured way. Based on the integration of fuzzy logic, causal analysis, distance-based ranking, and ranking aggregation techniques, the study provides a modern and practical model for supplier selection that is suitable for medium-scale automotive manufacturing environments.

2. Literature Review

Over the years, supplier selection has been one of the most widely studied topics in supply chain management, especially for industries where product quality and timely delivery are a concern [3, 26, 27]. Medium-scale automotive manufacturers are under enhanced pressure to identify suppliers who can fulfill technical requirements by providing consistent quality and supporting flexible production schedules at competitive prices [28, 29]. Because supplier performance is influenced by multiple strategic and operational factors, researchers often use MCDM approaches in structuring the evaluation process. In Table 1, a summary of various MCDM Tools is shown.

Table 1. Summarized table of various MCDM tools

MCDM Tool	Purpose	Strengths	Limitations	References
FAHP	Determines criteria weights under uncertainty	Captures expert ambiguity, handles linguistic terms, and is reliable for subjective judgments	Sensitive to inconsistency in pairwise comparisons	[30, 31]
FDEMATEL	Identifies cause-and-effect relationships among criteria	Highlights influential criteria, visual cause–and–effect mapping, supports strategic decisions	Requires expert knowledge; results depend on survey quality	[32]
TOPSIS	Ranks alternatives by distance from ideal and worst solutions	Simple, intuitive, fast computation, widely adopted	Sensitive to normalization and weight assignment	[33-35]
EDAS	Ranks alternatives based on positive and negative distance from the average	Works well when performance variation is small, stable outputs	Requires careful handling of average-based scoring	[31, 34, 36]
Borda Method	Aggregates rankings from different MCDM tools	Balances ranking variations, easy to compute	Ignores relative distances between ranks	[21-23]
Copeland Count	Voting-based final ranking aggregation	Robust, considers pairwise wins/losses, reduces bias	Computationally heavier for many alternatives	[21-23]

Automotive supply chains are known to be complex, with just-in-time production systems and severe performance specifications. Studies have documented that supplier selection in this industry is based on factors such as quality and cost, followed by delivery reliability, manufacturing capability, financial strength, and risk management [37, 38]. Medium-scale enterprises often have restricted availability of resources and therefore need to consider reliable decisioning frameworks that can minimize risk and enhance suppliers' consistency in performance. According to researchers, subjective judgments, market uncertainty, and constantly changing expectations on sustainability render traditional scoring methods inadequate [39-41]. The presence of these issues has motivated the application of fuzzy and integrated techniques of MCDM [6, 9, 42].

A large part of the literature uses FAHP to determine the weight of selection criteria. FAHP extends the classic AHP, developed by Saaty, by introducing fuzzy numbers that capture the ambiguity of expert judgments [43, 44]. FAHP was used in a supplier evaluation problem and demonstrated that fuzzy pairwise comparison enhances decision accuracy in uncertain environments. In automotive applications, FAHP supports managers in giving priority to the criteria such as quality, delivery flexibility, or technological capability, considering linguistic expert judgments. This technique is valued for its simplicity and compatibility when combined with other MCDM models [45].

The DEMATEL method identifies the cause-and-effect relationships among criteria. Coupled with fuzzy logic, this method captures expert uncertainty more fully [46, 47]. FDEMATEL is particularly useful in complex systems, such as supply chains, since interdependencies among criteria may affect decision outcomes [48, 49]. For instance, technical capability might drive product quality, which then affects delivery reliability. Wu and Lee (2007) illustrated how fuzzy DEMATEL can classify factors into cause and effect groups [15], as well as reveal the criteria that most strongly drive the system. In the context of automotive supplier evaluation, the method directs managers' attention to influential criteria rather than just criteria weights. Such insight aids firms in planning targeted improvements and in focusing scarce attention on what really matters.

TOPSIS stands for Technique for Order Preference by Similarity to Ideal Solution and is one of the most widely used MCDM tools for ranking alternatives. The method was developed by Hwang and Yoon (1981) [16] and evaluates alternatives with respect to their relative closeness to the ideal and negative-ideal solutions. Because of its simple structure, minimum computational load, and strong interpretability, TOPSIS has gained a wide acceptance in supplier selection research [18, 50, 51]. A fuzzy TOPSIS model was applied to supplier selection and concluded that the method performs well in environments characterized by imprecise data. In the automotive sector, TOPSIS has been used to rank suppliers based on quality, cost, and delivery criteria, offering a balanced evaluation framework suitable for medium-scale companies.

The EDAS method, proposed by Ghorabaee (2016) [19], is a relatively new MCDM technique that evaluates alternatives regarding their positive and negative distances from the average solution. It differs from other classic methods in that it does not consider the ideal solution, whereas it compares every supplier against the overall mean. Therefore, this method may highlight suppliers who perform consistently above the average and could be useful in industries characterized by a narrow dispersion of the variation in performance. Many publications were dedicated to the application of EDAS in the manufacturing and logistics fields, proving its strength in ranking the set of alternatives without complex computations. Very recently, EDAS has been combined with fuzzy frameworks in order to enhance robustness in uncertain decision-making environments [52-54].

When various MCDM methods are combined, their ranking results sometimes do not coincide. Then, certain methods for aggregation of the results of ranking have been proposed. Bodra's method reduces rankings from multiple tools to a consensus order. It operates as the positional value of each alternative is calculated and then aggregated. Bodra's method is less common in automotive research; however, it has been used in engineering decision-making when there was a need to reconcile several ranking outputs. The Copeland Count is derived from the voting theory and works by aggregating rankings through pairwise comparisons. Each supplier receives points for wins or losses against other suppliers under each ranking method. The alternative granting the highest total score is placed at the top of the final ranking list. Several studies show that Copeland Count improves decision stability and reduces the influence of outliers from individual ranking techniques [21-23]. Using Bodra and Copeland Count consolidates supplier selection results in FAHP, FDEMATEL, TOPSIS, and EDAS, yielding more reliable final decisions.

New methodologies having hybrid models like FAHP + DEMATEL+TOPSIS, FAHP + EDAS, Fuzzy AHP + VIKOR, and other fuzzy integration approaches in supplier evaluation were also introduced. A comparative analysis of recent works (2020-2024) describes that most of the theories are focused on either weight assignment issues or other ranking processes, but there are very limited approaches that manage all tasks of uncertainty modeling, causal analysis, dual ranking validation, and rank aggregation in a single procedural flow. This paper has special importance as it combines FAHP, FDEMATEL, TOPSIS, EDAS, and rank aggregation in a single decision support model suitable for medium-scale Indian automobile companies.

Medium-scale automotive manufacturers rely on their suppliers for materials, components, and services. These firms have to bear cost pressure, volatile demand, and high-quality expectations. The choice of an appropriate supplier is problematic due to the many relevant selection criteria, including quality, delivery reliability, technical capability, financial stability, sustainability, and risk factors. These criteria are interdependent and very often evaluated under incomplete or uncertain information.

Traditional supplier selection methods fail to handle ambiguity, do not consider the causal relationships between criteria, and very often rely on single ranking methods that result in inconsistent results. The medium-scale firm requires a structured and dependable framework that is able to manage uncertainty, capture expert knowledge, and yield reliable rankings. An integrated approach based on fuzzy logic, causal analysis, multiple ranking techniques, and ranking aggregation is required to enhance the accuracy and robustness of supplier selection decisions in medium-scale automotive firms.

Although several models are presented in the literature for the evaluation of suppliers, most of these studies address only separate parts of the whole decision process. Most studies use FAHP or AHP in order to determine the weights of the criteria. However, no study has considered the causal relationship among the criteria. In reality, factors such as technical capability, quality performance, and delivery reliability influence one another. Without identifying these interdependencies, the criteria weighting is incomplete.

At the same time, many works utilize fuzzy TOPSIS, VIKOR, or EDAS to rank suppliers, since each of the methods brings out different results because of its distance or deviation measuring technique. Reliance on one ranking tool increases the possibility of inconsistent decisions. Only a few works incorporate ranking aggregation techniques, such as Borda or Copeland Count, in order to provide a consensus ranking when multiple MCDM outputs are available.

Research integrating FAHP and FDEMATEL is present but mainly applied to large-scale industries or green supply chains. Medium-scale automotive manufacturers face completely different environmental challenges. They work with limited resources and fewer automated systems with an increased exposure to supplier risk. In such a context, studies focusing on medium-scale automotive units are rather scarce. These firms require decision models that work well with uncertain judgments, smaller datasets, and practical implementation constraints.

Table 2. Gap analysis for supplier selection

Literature Theme	What Existing Studies Have Done	Identified Gaps	Gap Addressed in This Study
Criteria Weighting	FAHP, AHP, and ANP were used to derive weights for supplier criteria	Limited work on combining FAHP with causal analysis to refine weights	Uses FAHP + FDEMATEL to obtain weights and understand cause–and–effect relations
Handling Uncertainty	Fuzzy methods are widely used but mostly applied in isolation	A few hybrid frameworks combining multiple fuzzy and ranking tools	Develops a combined FAHP + FDEMATEL + TOPSIS + EDAS framework
Supplier Ranking Methods	TOPSIS and EDAS are often used separately	Lack of cross-verification using multiple ranking models	Uses TOPSIS and EDAS together for ranking validation
Ranking Aggregation	Borda and Copeland are rarely used in automotive supplier selection	Limited evidence of consolidated ranking when multiple MCDM outputs conflict	Combines Borda and Copeland Count for stable consensus ranking
Automotive Industry Focus	Most models are applied in large OEMs; fewer studies are on medium-scale automotive units.	Medium-scale firms have distinct constraints and limited resources	Modifies the hybrid model to medium-scale automotive conditions
Sensitivity Analysis	Often missing from supplier selection models	Rankings are rarely tested for robustness under changing weights	Performs sensitivity analysis to test model stability
Integrated Hybrid Models	Existing works focus on 1 or 2 MCDM combinations.	No comprehensive model using FAHP + FDEMATEL + TOPSIS + EDAS + Borda + Copeland	Proposes a complete integrated framework with all these tools

Another serious gap in the current literature is related to the scarce use of sensitivity analysis. Sometimes, variations in criteria weights or in expert opinions may alter supplier ranking, but only a few models test the stability of the results. This reduces the reliability of their recommendations. Overall, the literature lacks an integrated model that includes FAHP for criteria weighting, FDEMATEL for causal analysis, TOPSIS and EDAS for ranking, and Borda with Copeland Count for consensus building, which also encompasses sensitivity analysis. Addressing such gaps, as shown in Table 2, can notably strengthen decisions pertaining to supplier selection for medium-scale automotive industries.

The study deals with the supplier selection in medium-scale automotive manufacturing units, wherein procurement decisions directly affect production efficiency, cost control, and product quality. The scope of the model encompasses raw materials, components, and service suppliers relevant to automotive operations. The qualitative criteria, such as quality, delivery reliability, cost, capability, financial stability, sustainability, and risk, are dealt with. It uses expert inputs to handle uncertainty while conducting the analysis based on fuzzy logic, causal modeling, distance-based ranking, and ranking aggregation. Specifically excluded from the scope of this study are large-scale OEMs, very extensive global supply networks, and highly automated procurement systems. On the contrary, the core of the investigation is very practical with data-light methods, best suited to medium-scale firms operating under resource and information constraints. This proposed framework integrates various decision-making tools that are usually applied separately. The novelty lies in integrating FAHP, FDEMATEL, TOPSIS, EDAS, Borda, and Copeland Count into one unified supplier selection model designed specifically for medium-scale automotive industries. FAHP captures uncertainty in expert judgment, while FDEMATEL, in turn, portrays the causal structure among the criteria, thus fortifying the validity of the weight assignment. The combined use of the TOPSIS and EDAS technique offers a dual approach to evaluation, reducing model bias. Borda and Copeland Count provide a consolidated ranking that overcomes inconsistencies between individual MCDM tools. This is further backed by sensitivity analysis, ensuring the final ranking is robust under variation in value conditions. The tailored focus on medium-scale automotive units adds practical novelty since most existing studies address large enterprises or general manufacturing systems.

3. Proposed Methodology

This study applies a structured MCDM approach to evaluate and rank suppliers for the medium-scale automotive industry. The proposed methodology, as shown in Figure 1, integrates FAHP, FDEMATEL, TOPSIS, EDAS, Bodra aggregation, Copeland Count, and sensitivity analysis into one methodology. The flow of work is designed to capture expert judgments, quantify uncertainty, and provide a balanced and validated ranking of suppliers.

3.1. Criteria and Alternatives Identification

The ten factors employed in this analysis are also valid in current literature on automobile supplier analysis, in which quality, delivery performance, cost, risk, capability, and sustainability are highlighted as prominent considerations. All ten factors are supportive of best practices in the automobile industry, as well as company internal practices for purchasing. The five suppliers analyzed are part of the actual supplier pool for the component category chosen.

3.2. Fuzzy Analytic Hierarchy Process

FAHP is applied to compute the importance weights of the criteria under uncertainty. Experts compare each pair of criteria using TFNs. A TFN is expressed as: $\tilde{A}$=(l, m, u)
The fuzzy pairwise comparison matrix is:

$$\tilde{A}=[\tilde{a}_{ij}],\ \tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij},)$$

Normalized FAHP weights are derived using:

$$w_i = \frac{d_i}{\sum_{i=1}^{n} d_i}$$

3.3. FUZZY DEMATEL

FDEMATEL is used to determine the causal relationships among criteria. Experts provide fuzzy direct-influence scores between criteria using TFNs.

The initial fuzzy direct-influence matrix is: $\tilde{X} = [\tilde{x}_{ij}]$

Normalization is performed using: $\tilde{N} = \frac{\tilde{X}}{max_i \sum_j u_{ij}}$

The total relation matrix is computed as:

$$\tilde{T} = \tilde{N}(I - \tilde{N})^{-1}$$

The prominence and relation values are:

$$D_i = \sum_j t_{ij},\ R_i = \sum_j t_{ji}$$

Prominence: Pi=Di+Ri, and Relation: Ei=Di-Ri

FAHP is employed solely for determining criterion weights, whereas FDEMATEL unveils cause-and-effect relations among criteria in order to confirm the logical structure of criterion weights.

3.4. TOPSIS

TOPSIS ranks suppliers based on closeness to the ideal solution.

The normalized decision matrix is: $r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$

Weighted normalization: $v_{ij} = w_j r_{ij}$

Ideal best and worst:

$$A^+ = \{\max(v_{ij})\}, A^- = \{\min(v_{ij})\}$$

Distances:

$$D_i^+ = \sqrt{\sum_j (v_{ij} - A_j^+)^2}\ \ D_i^- = \sqrt{\sum_j (v_{ij} - A_j^-)^2}$$

Relative closeness: $C_i = \frac{D_i^-}{D_i^+ + D_i^-}$

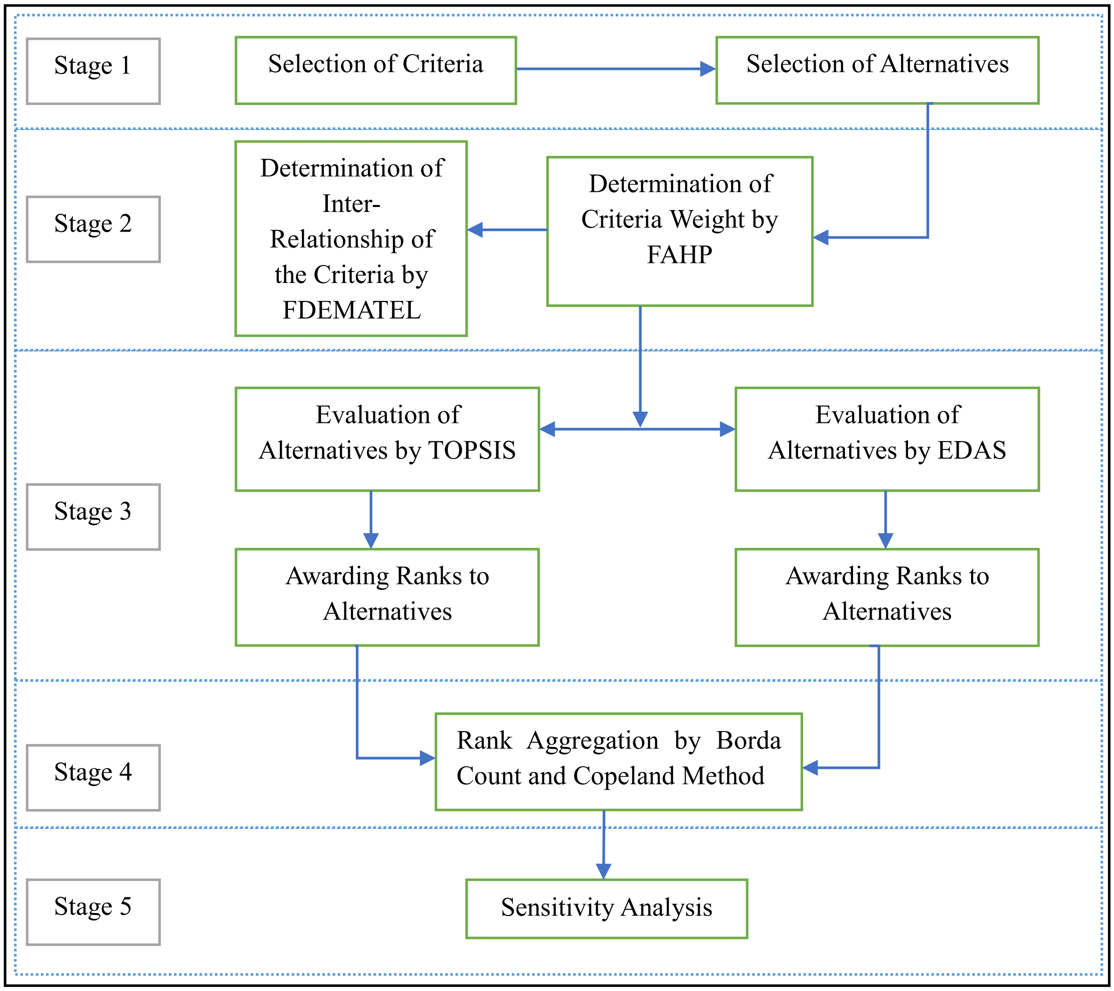

Fig. 1 Proposed methodology

3.5. EDAS

EDAS evaluates alternatives using deviation from the average solution.

Average solution: $AV_j = \frac{1}{m}\sum_i x_{ij}$

Positive and negative distances:

$$PDA_{ij} = \max\left(0, x_{ij} - AV_j\right),$$
$$NDA_{ij} = \max(0, AV_j - x_{ij})$$

Weighted EDAS scores lead to a supplier ranking.

3.6. Bodra Aggregation and Copeland Count

The rankings from FAHP-TOPSIS and FAHP-EDAS are combined using Bodra's method, which assigns cumulative points based on position.

$$Borda\ Score = \sum_{j=1}^{k}(m - r_{ij} + 1)$$

Copeland Count validates the final ranking using:

$$CC_i = W_i - L_i$$

Where W_i is the number of pairwise wins and L_i is the number of losses.

These rank aggregation methods make it easier to resist outlier values and counter sensitivity, forming a common opinion that is easy for a professional to understand.

3.7. Sensitivity Analysis

Weights are varied within a reasonable range (±10 to ±20 percent). The stability of the ranking indicates the robustness of the model.

4. Results and Discussion

This article presents a medium-scale automotive manufacturing unit situated in eastern India, engaged in the manufacture of sub-assemblies. The company is highly dependent on outsourced components, including stamped parts, machined parts, fasteners, fabrication items, and electrical sub-assemblies. Supplier performance has a direct effect on the continuity of production, cost competitiveness, and quality of the final product. A pressing need for a transparent and systematic supplier evaluation framework led the management to apply an MCDM approach using FAHP, FDEMATEL, TOPSIS, EDAS, Bodra, and Copeland Count.

The company normally operates with more active suppliers; however, for strategic sourcing, management wanted to identify the best-performing vendors from a shortlist of five major suppliers. These suppliers, labeled S1, S2, S3, S4, and S5, provide essential items with high annual consumption and moderate to high criticality. Although the company already maintains a supplier scorecard system, it is mainly descriptive in nature and lacks an integrated structure that can deal with trade-offs such as quality versus cost or reliability versus innovation. Hence, the proposed MCDM framework has been used to support a strategic sourcing decision for the next financial year. Ten criteria, as shown in Table 3, were chosen after expert consultations.

These criteria reflect both the operational and strategic expectations typical in a medium-scale automotive environment. A panel of a few experts participated in pairwise comparisons and influence assessment. Each expert provided linguistic judgments such as equally important, moderately more important, and strongly more important, mapped to triangular fuzzy numbers, as shown in Table 4.

Table 3. List of criteria and their description

Criteria	Notation	Description
Quality	C1	Measures defect rate, conformance to specifications, consistency, and inspection results. It is usually the most critical factor in automotive manufacturing.
Cost	C2	Includes unit price, cost stability, discount structure, and total cost of ownership. Helps maintain competitiveness in the supply chain.
Delivery Reliability	C3	Evaluates on-time delivery, schedule adherence, and delivery flexibility. Delays affect inventory and production flow.
Technical Capability	C4	Assesses machinery capability, process stability, design support, and technological know-how necessary for automotive components.
Financial Stability	C5	Reviews liquidity, debt structure, cash flow, and financial risk. Ensures long-term supply reliability.
Production Capacity	C6	Indicates the supplier's ability to meet volume demands, flexibility during peak periods, and response to urgent orders.
Sustainability and Environmental Compliance	C7	Considers green practices, energy efficiency, waste reduction, and adherence to environmental regulations. Important for ESG and automotive compliance.
Risk Management	C8	Measures supply continuity, contingency planning, disruption response, and operational risk mitigation.
Supplier Relationship and Communication	C9	Covers responsiveness, communication quality, transparency, and long-term collaborative behavior.
Innovation Capability	C10	Refers to the supplier's ability to introduce new processes, materials, and cost-saving improvements. Supports continuous improvement in automotive development.

Table 4. Pairwise comparisons among the various criteria

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
C1	1	5	3	4	5	4	7	3	3	5
C2	1/5	1	2	3	2	2	3	2	2	2
C3	1/3	1/2	1	2	3	3	3	3	2	2
C4	1/4	1/3	1/2	1	2	3	5	2	2	3
C5	1/5	1/2	1/3	1/2	1	2	2	3	2	2
C6	1/4	1/2	1/3	1/3	1/2	1	2	2	2	2
C7	1/7	1/3	1/3	1/5	1/2	1/2	1	2	2	3
C8	1/3	1/2	1/3	1/2	1/3	1/2	1/2	1	1/2	7
C9	1/3	1/2	1/2	1/2	1/2	1/2	1/2	2	1	2
C10	1/5	1/2	1/2	1/3	1/2	1/2	1/3	1/7	1/2	1

This section presents the results of the FAHP, FDEMATEL, TOPSIS, and EDAS methods, and final aggregation using the Borda and Copeland methods. The analysis covers criteria weight estimation, causal relationships, supplier ranking behaviour, and stability of the results through sensitivity analysis.

4.1. Computation of FAHP Weights

The weights of the criteria were calculated by FAHP based on expert pairwise judgments. The normalized weights are as presented in Figure 2.

The results indicate that three influential criteria are Quality (0.279), Delivery Reliability (0.130), and Cost (0.128). This corresponds to the operational needs of medium-scale automotive units, where defect-free components and timely supplies, along with competitive pricing, have direct impacts on production continuity and cost efficiency. On the other hand, Innovation Capability, with a weight of 0.036 and Sustainability Compliance at 0.052, received lower weights. This is expected for medium-scale units still strengthening their fundamental production processes before prioritizing long-term strategic capabilities.

4.2. Cause–Effect Analysis Using FDEMATEL

The FDEMATEL method was used to find interdependencies among the ten criteria. The results classify each criterion as a cause or effect, as shown in Figure 3. The results identify technical capability, financial stability, production capacity, risk management, supplier relationship, sustainability, and innovation capability as the cause group. These factors drive the performance results but are not directly shaped by the other criteria. Suppliers with strong technical capability tend to produce higher-quality parts. Financially stable suppliers tend to be the ones who ensure delivery reliability. Effective risk management thus reduces disruptions to supply, improving delivery performance. Robust communication sparks coordination, hence improving quality while reducing delays.

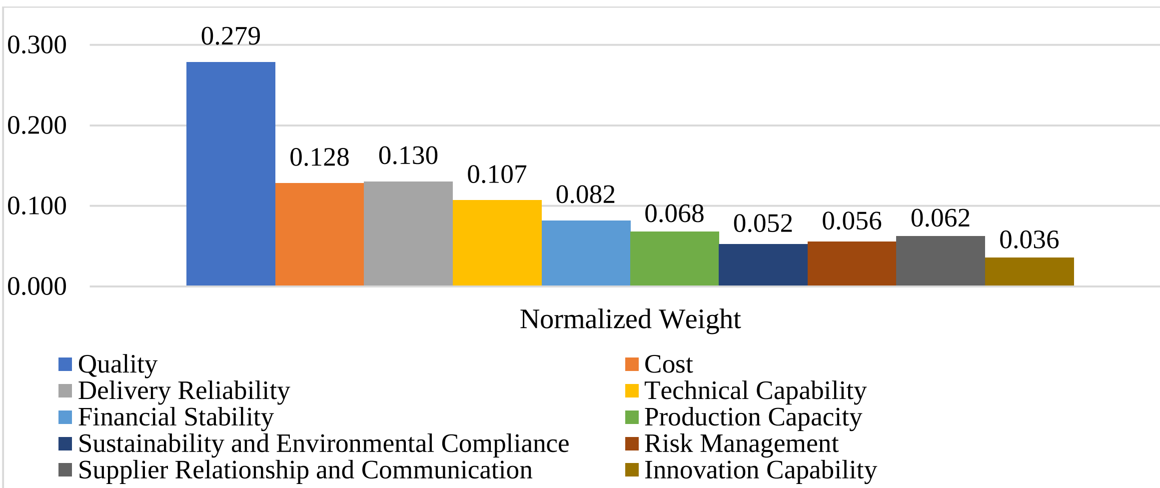

Fig. 2 Computed normalized weight by FAHP

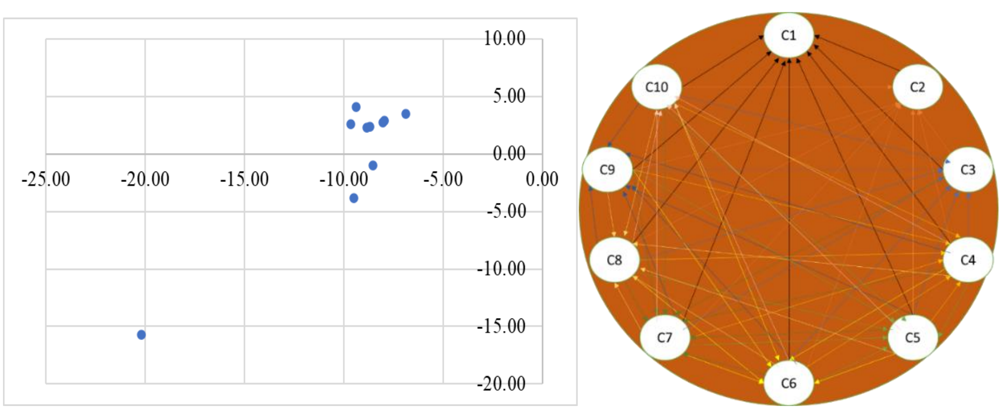

Fig. 3 Inter-relationship among criteria by FDEMATEL

In contrast, Quality, Cost, and Delivery Reliability are categorized into the effect group, since they are observable results influenced by cause criteria. This corresponds to the reasoning of the automotive industry: only when a supplier is technically strong, has good financial health, and is adequately operationally capable can it provide supplies of high quality, at timely and cost-effective levels.

The FDEMATEL findings help to validate the FAHP weightage by confirming that the highly weighted criteria, such as quality, cost, and delivery, are outcomes, while many lower-weighted criteria actually serve as the underlying drivers. This supports a coherent and realistic interpretation of supplier behaviour.

4.3. Supplier Ranking Using TOPSIS, EDAS

The performance scores of the five suppliers (S1 to S5) were evaluated through TOPSIS and EDAS. Both methods presented ranking with respect to the closeness to the ideal solution in TOPSIS and deviation from the average solution in EDAS. The summarized ranking results are shown in Figure 4.

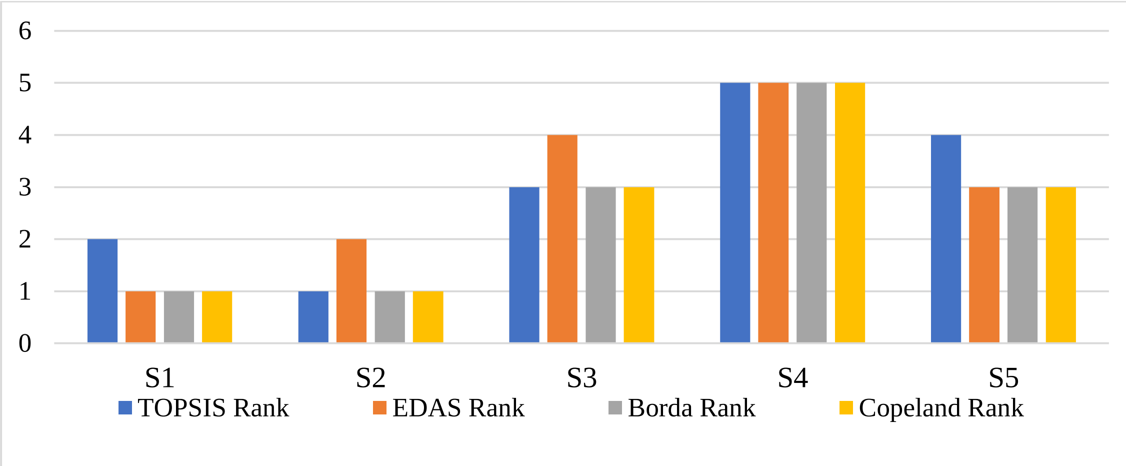

Fig. 4 Ranking distribution

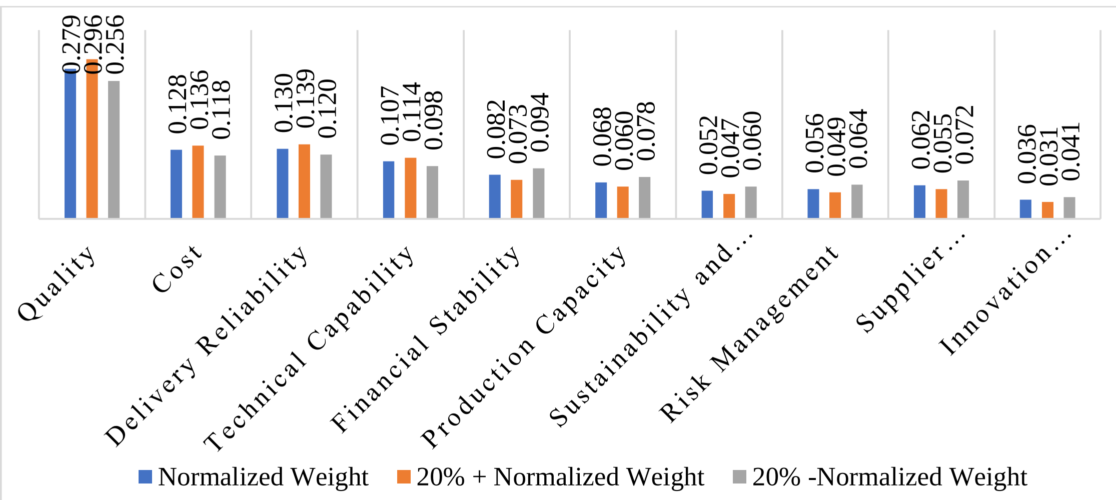

Fig. 5 Normalized weightage distribution for sensitivity analysis

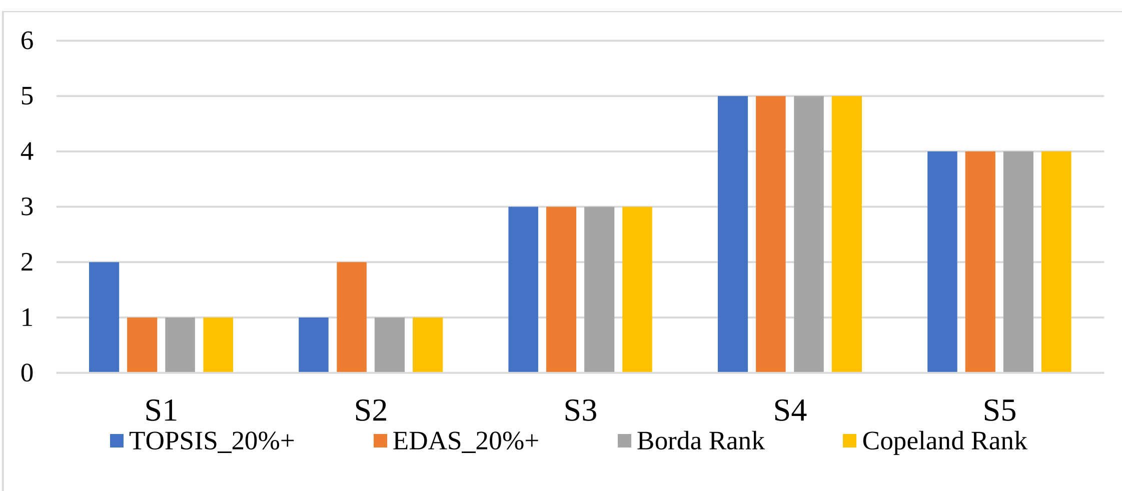

Fig. 6 Sensitivity scenario +20% weightage

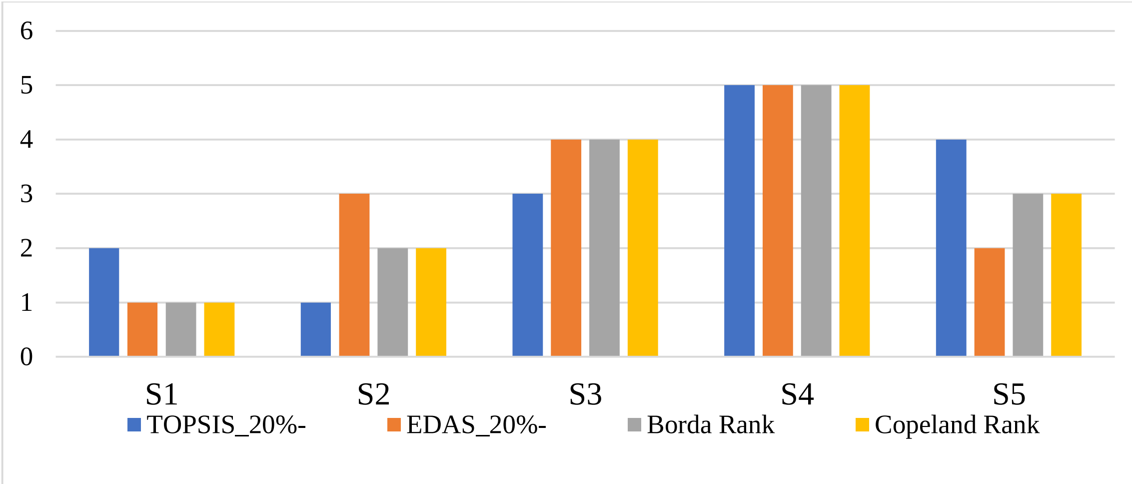

Fig. 7 Sensitivity scenario -20% weightage

By TOPSIS, the best-ranked supplier was S2, followed by S1, while S1 ranked first and S2 second according to EDAS. Since this ranking slightly differs, it is quite normal because of the nature of these methods; while TOPSIS amplifies criteria with large positive distance from the ideal, EDAS balances the positive and negative deviation relative to the average.

To combine the rankings, a Borda count method was used. TOPSIS and EDAS ranks were converted into Borda scores, and the sum total of scores was used to create a consensus ranking. S1 and S2 had the highest Borda score, further confirming them as the two best-performing suppliers.

Further validating this, the method by Copeland was used to compare suppliers pairwise. Again, S1 and S2 had the highest Copeland scores, reinforcing the conclusion. S1 and S2 constantly emerge at the top with strong overall capabilities in all criteria. S3 and S5 form a cluster of medium performers, sometimes shifting position according to the method applied.

S4 always comes last, which indicates significant shortcomings in several criteria and needs to be addressed. The strong agreement between Borda and Copeland confirms that the integrated ranking is reliable and suitable for managerial decision-making.

4.4. Sensitivity Analysis

Sensitivity analysis was performed to identify how stable the ranking of suppliers remains when weights normalized through FAHP are increased and decreased by 20% of the computed original weightage, as shown in Figure 5. Using these modified weights, TOPSIS and EDAS were again run, followed by a ranking aggregation using the Borda and Copeland methods. This approach ensures that the final supplier decision is robust under fluctuating decision-maker preferences.

The first scenario applies a 20 percent increase to all the criteria weights. The results of that are shown in Figure 6. S1 and S2 are the two best suppliers, ranked first and second, respectively, across all MCDM methods, such as TOPSIS, EDAS, Borda, and Copeland.

S3 and S5 retain their middle-order positions, without any shift, even with increased weights. S4 remains the lowest-rated supplier, reflecting consistent performance gaps. This would mean that the model is stable when weights increase, and supplier rankings do not change much.

The second scenario applies a 20 percent decrease to all the criteria weights. The results of that are shown in Figure 7. S1 is the best-ranked supplier, and its ranking has not changed across TOPSIS, EDAS, Borda, and Copeland. S2 drops slightly in EDAS to Rank 3, but remains in the top two in aggregated Borda and Copeland rankings.

S5 improved in EDAS ranking to 2nd position but finally settled at Rank 3 after aggregation. S3 remains mid-ranked, and S4 always stays last. The minor reordering between S2, S3, and S5 in EDAS shows that EDAS is slightly more sensitive to weight reductions but returns a stable and rational result from an aggregated ranking.

S1 and S2 always show the best performance under all conditions. The methods of Borda and Copeland classify them, independent of any weight changes, as the top performers. Their dominance confirms resilience against uncertainty in the criteria weight assignment.

S5 exhibits a moderate sensitivity in the -20 percent case when it briefly rises to EDAS Rank 2. However, it outperforms neither S1 nor S2 on any aggregate ranking. S4 confirms persistent performance gaps and remains positioned as the lowest-ranked supplier in all methods and scenarios.

Aggregated rankings using Borda and Copeland smooth out minor fluctuations from TOPSIS and EDAS. The fact that S1 and S2 are consistent at the top justifies a recommendation as preferred suppliers. The chronic bottom performance of S4 underlines the need for significant improvement in the supplier panel. The small ranking shift of S5 suggests that this supplier could be a reasonable alternative if the preference over weights changed in actual practice.

5. Conclusion

This article provides the latest and most reliable methodology based on a creative approach for the assessment of suppliers for medium-sized automotive manufacturers. Since sourcing quality, cost control, and operational stability are critical to performance accomplishment in the automotive sector, this article uses FAHP, FDEMATEL, TOPSIS, and EDAS to illustrate the complex trade-offs that purchasing teams face in real-world settings. Each technique brought distinct strengths: TOPSIS and EDAS created two independent but complementary performance rankings, FAHP quantified expert judgment under uncertainty, and FDEMATEL emphasized the cause-and-effect structure among the criteria. Compared to utilizing a single tactic, the combined approach generated better balance and defensibility.

In this article, a comprehensive and reliable supplier evaluation framework through an innovative proposed model for medium-scale automotive industries was developed. Since the performance attainment in the automotive industry greatly relies on the sourcing quality, cost control, and operational stability, this research integrates FAHP, FDEMATEL, TOPSIS, and EDAS to capture the complex trade-offs that purchasing teams face in real conditions. Each of the methods brought in different strengths: FAHP quantified expert judgment under uncertainty, while FDEMATEL clarified the cause-and-effect structure among the criteria, and TOPSIS and EDAS produced two independent yet complementary rankings for performance. The combined approach created more balance and defensibility in comparison to using a single method.

The criteria used in the model encompassed the full range of aspects of supplier capability: quality, cost, delivery reliability, technical strength, financial stability, capacity, environmental compliance, risk management, communication, and innovation. FAHP weights illustrated that quality and delivery reliability remain two of the most influential factors in automotive supply chains, while sustainability and innovation also bear increasing strategic value. FDEMATEL helped to identify the causes that operate as dependent performance outcomes. This insight is useful for managers who need to design supplier development programs and allocate resources to the most impactful areas.

The outputs from TOPSIS and EDAS showed consistency, where top performers remained in their positions as obtained under both methods. In persistence, to make sure that such are reliable, Borda and Copeland aggregation techniques have been applied in combination rankings originating from different models. This present step reduces methodological bias and emphasizes suppliers whose performance is consistent across multiple views of evaluation. The best performing suppliers were clearly identified in the aggregate output as showing consistency in the strength of technical capability, delivery performance, and overall operational maturity.

Sensitivity analysis strengthened the conclusions. Increasing and decreasing FAHP weights by 20% tested how much the shift in decision-maker priorities would alter the ranking. High stability was observed, especially for top and bottom-ranked suppliers. Minor variations appeared among only mid-level suppliers, as is generally expected when weight preferences shift. It was confirmed hereby that the proposed evaluation system is robust and suitable for practical use in medium-scale automotive industries.

The integrated methodology provides clear insights into interdependent performance elements, lowers the risk of subjective bias, and generates trustworthy evaluations to assist strategic sourcing decisions. By putting this approach into practice, automotive units will see an improvement in the consistency of their suppliers' performance and a greater alignment with operational goals, resulting in the development of more significant long-term partnerships throughout the supply chain.

5.1. Future Scope and Limitations

Although the framework developed herein is comprehensive, a few limitations remain that could be addressed in future work. Such an approach captures domain knowledge; it can also introduce biases where the number of experts is not high or not representative of the industry. Future research can expand the expert pool, include multi-level decision makers, or apply data-driven weighting techniques to reduce reliance on subjective inputs.

Future studies can also be directed to developing decision dashboards, software modules, or automated evaluation systems to facilitate easy adoption of this framework by industries. The proposed framework provides a solid backbone for improvement to the supplier evaluation and several promising research ways in deeper, broader, and more adaptive decision-making systems.

The limitations are that only FAHP, FDEMATEL, TOPSIS, and EDAS were used. Although this combination provides strong coverage, additional techniques like DEA, PROMETHEE, GRA, or MOORA may be incorporated for a comparison between efficiency-based results and preference-based results. Hybrid models, including fuzzy extensions, may also improve handling of extreme uncertainty.

References

[1] Anjali Awasthi, Satyaveer S. Chauhan, and S.K. Goyal, "A Fuzzy Multicriteria Approach for Evaluating Environmental Performance of Suppliers," *International Journal of Production Economics*, vol. 126, no. 2, pp. 370-378, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[2] Konrad Zimmer, Magnus Fröhling, and Frank Schultmann, "Sustainable Supplier Management – A Review of Models Supporting Sustainable Supplier Selection, Monitoring and Development," *International Journal of Production Research*, vol. 54, no. 5, pp. 1-31, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[3] K. Balakannan et al., "Selection and Evaluation of Supplier by Decision Model of Hybrid Data Envelopment Analysis," *International Journal of Applied Engineering Research*, vol. 10, no. 62, pp. 123-127, 2015. [Google Scholar]

[4] Rahul Verma, "Supply Chain Management: Optimising Efficiency and Sustainability in the Supply Network," *Journal of Advanced Management Studies*, vol. 1, no. 2, pp. 13-18, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[5] Krishnendu Mukherjee, "Supplier Selection Criteria and Methods: Past, Present and Future," *International Journal of Operational Research*, vol. 27, no. 1-2, pp. 356-373, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[6] Kannan Govindan et al., "Multi-Criteria Decision Making Approaches for Green Supplier Evaluation and Selection: A Literature Review," *Journal of Cleaner Production*, vol. 98, pp. 66-83, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[7] Mohamed Abdel-Basset et al., "A Hybrid Approach of Neutrosophic Sets and DEMATEL Method for Developing Supplier Selection Criteria," *Design Automation for Embedded Systems*, vol. 22, no. 3, pp. 257-278, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[8] Forum Jalundhwala, and Vaishali Londhe, "A Systematic Review on Implementing Operational Excellence as a Strategy to Ensure Regulatory Compliance: A Roadmap for Indian Pharmaceutical Industry," *International Journal of Lean Six Sigma*, vol. 14, no. 4, pp. 730-758, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[9] Chia-Nan Wang et al., "Multi-Criteria Decision Making (MCDM) Model for Supplier Evaluation and Selection for Oil Production Projects in Vietnam," *Processes*, vol. 8, no. 2, pp. 1-13, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[10] F.Z. Gherbi et al., "The Application of the Fuzzy Analytical Hierarchy Process (FAHP) as a Multi-Criteria Analysis Tool for Road Risk Assessment: Algeria as a Case Study," *Studies in Engineering and Exact Sciences, South Florida Publishing LLC*, vol. 5, no. 2, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[11] Lin Wang, Jianying Xiong, and Chenglu Ruan, "Research on Product Design of FAHP Bone Marrow Aspiration Needle," *Heliyon*, vol. 10, no. 5, pp. 1-12, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[12] Irina Vinogradova-Zinkevič, Valentinas Podvezko, and Edmundas Kazimeras Zavadskas, "Comparative Assessment of the Stability of AHP and FAHP Methods," *Symmetry*, vol. 13, no. 3, pp. 1-25, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[13] Fawaz M. Abdullah, Abdulrahman M. Al-Ahmari, and Saqib Anwar, "An Integrated Fuzzy DEMATEL and Fuzzy TOPSIS Method for Analysing Smart Manufacturing Technologies," *Processes*, vol. 11, no. 3, pp. 1-19, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[14] Mamta Pandey, Ratnesh Litoriya, and Prateek Pandey, "Application of Fuzzy DEMATEL Approach in Analysing Mobile App Issues," *Programming and Computer Software*, vol. 45, no. 5, pp. 268-287, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[15] Wei-Wen Wu, and Yu-Ting Lee, "Developing Global Managers' Competencies Using the Fuzzy DEMATEL Method," *Expert Systems with Applications*, vol. 32, no. 2, pp. 499-507, 2007. [CrossRef] [Google Scholar] [Publisher Link]

[16] Ching-Lai Hwang, and Kwangsun Yoon, "Methods for Multiple Attribute Decision Making," *Multiple Attribute Decision Making*, vol. 186, pp. 58-191, 1981. [CrossRef] [Google Scholar] [Publisher Link]

[17] Babak Zolghadr-Asli, Omid Bozorg-Haddad, and Nora van Cauwenbergh, "Multi-Attribute Decision-Making: A View of the World of Decision-Making," *Essential Tools for Water Resources Analysis, Planning, and Management*, pp. 305-322, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[18] Chen-Tung Chen, Ching-Torng Lin, and Sue-Fn Huang, "A Fuzzy Approach for Supplier Evaluation and Selection in Supply Chain Management," *International Journal of Production Economics*, vol. 102, no. 2, pp. 289-301, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[19] Mehdi Keshavarz Ghorabaee et al., "Extended EDAS Method for Fuzzy Multi-Criteria Decision-Making: An Application to Supplier Selection," *International Journal of Computers Communications & Control*, vol. 11, no. 3, pp. 358-371, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[20] Hossein Ghanbari et al., "Selecting a Sustainable Hydrogen Production Method Using a Novel Dual Evaluation EDAS Approach," *Annals of Operations Research*, pp. 1-42, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[21] Wojciech Sałabun, and Karol Urbaniak, "A New Coefficient of Rankings Similarity in Decision-Making Problems," *Computational Science - ICCS 2020*, pp. 632-645, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[22] Mohammad Azadfallah, "A New Aggregation Rule for Ranking Suppliers in Group Decision Making under Multiple Criteria," *Journal of Supply Chain Management Systems*, vol. 5, no. 4, pp. 38-48, 2016. [Google Scholar] [Publisher Link]

[23] Yousef Elsheikh, Yousef Alqasrawi, and Mohammad Azzeh, "On Obtaining a Stable Vote Ranking Methodology for Implementing E-Government Strategies," *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 6, pp. 3379-3392, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[24] S.S. Jadhav, and Jai Prakash, "Analyzing Financial Trends in the Contemporary Automobile Industry in India," *Innovative Research Thoughts*, vol. 9, no. 5, pp. 368-374, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[25] Mohamad Aridho, and Sutrisno Sutrisno, "Review of Supply Chain Management (SCM) Performance at PT. BJ," *STRING (Technology Research and Innovation Writing Unit)*, vol. 8, no. 3, pp. 339-347, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[26] Arinda P. Rachman et al., "Comparison of Multi-Criteria Decision-Making Methods for Selection of Optimum Passive Design Strategy," *Energy and Buildings*, vol. 314, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[27] Seyed Mohammad Hossein Zakeri et al., "Developing an MCDM Model for the Benefits, Opportunities, Costs and Risks of BIM Adoption," *Sustainability*, vol. 15, no. 5, pp. 1-19, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[28] Yildiz Özcan, and Şebnem İndap, "Bibliometric Analysis of Publications on Sustainable Supplier Selection in the Context of Supply Chain Management," *International Review of Economics and Management*, vol. 12, no. 1, pp. 67-89, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[29] Mason Cooper, "Understanding Supplier Selection Criteria: Perspectives from Procurement Professionals in Diverse Industries," *Preprint*, pp. 1-12, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[30] S. Raziei, "EFQM Excellence Model Based on Multi-Criteria Processes Fuzzy Ahp, Fuzzy Dematel, Fuzzy Topsis, and Fuzzy VIKOR; A Comparative Survey," *International Journal of Scientific & Technology Research*, vol. 8, no. 4, pp. 248-260, 2019. [Google Scholar] [Publisher Link]

[31] V. Alpagut Yavuz, "An Analysis of Job Change Decision Using a Hybrid Mcdm Method: A Comparative Analysis," *International Journal of Business and Social Research*, vol. 6, no. 3, pp. 60-75, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[32] M. Madanchian, and H. Taherdoost, "Applications of Multi-Criteria Decision Making in Information Systems for Strategic and Operational Decisions," *Computers*, vol. 14, no. 6, pp. 1-21, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[33] Nimet Yapici Pehlivan et al., "A Comparative Study of Integrated FMCDM Methods for Evaluation of Organizational Strategy Development," *Journal of Business Economics and Management*, vol. 19, no. 2, pp. 360-381, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[34] Svetla Stoilova, "A New Aggregated Multi-Criteria Approach for Evaluation of the Autonomous Metro Systems' Performance in the European Countries," *Symmetry*, vol. 14, no. 10, pp. 1-34, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[35] Nuh Keleş, "A Multi-Criteria Decision-Making Framework Based on the MEREC Method for the Comprehensive Solution of Forklift Selection Problem," *Eskisehir Osmangazi University Journal of Economics and Administrative Sciences*, vol. 18, no. 2, pp. 573-590, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[36] R. Vavrek, "Efficiency and Inefficiency of Public Administration," *Journal of Economic Development, Environment and People*, vol. 7, no. 1, pp. 6-14, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[37] G. Muniraju, and A. Muthumoni, "Growth and Performance of India's Automobile Industry in India - A Comprehensive Review," *Shanlax International Journal of Arts, Science and Humanities*, vol. 12, no. S1, pp. 163-167, 2024. [CrossRef] [Publisher Link]

[38] Kalpesh S. Kamble, and Vinay Chandra Jha, "A Study on Evolution and Structure of Indian Automobile Industry," *ShodhKosh Journal of Visual and Performing Arts*, vol. 5, no. 6, pp. 1668-1674, 2024. [CrossRef] [Publisher Link]

[39] Kamal Joshi et al., "Measuring the Intensity of Challenges and Problems of Small-Scale Entrepreneurs in Uttarakhand, India," *Vilakshan-XIMB Journal of Management*, vol. 22, no. 2, pp. 217-233, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[40] P. Mubarak Rahman et al., "Driving Efficiency through Innovation: Exploring Dynamic Capabilities in Indian Manufacturing Small and Medium Scale Enterprise," *Cogent Business & Management*, vol. 12, no. 1, pp. 1-19, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[41] Mukesh Kumar et al., "The Adoption of Artificial Intelligence Powered Workforce Management for Effective Revenue Growth of Micro, Small, and Medium Scale Enterprises (MSMEs)," *Production Planning & Control*, vol. 35, no. 13, pp. 1639-1655, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[42] D. Sobya, and S. Jeyabalan, "Enhancement of Production Rate and Flexibility in an Assembly Line by Execution of Various Lean Techniques-A Case Study," *International Journal of Engineering Research in Africa*, vol. 51, pp. 15-27, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[43] Seife Ebeyedengel, "Application of FAHP Methodology to Rank Productivity-Affecting Factors in Blanket Factory: A Case Study," *Advances in Operations Research*, vol. 2023, no. 1, pp. 1-13, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[44] Mahmoud Z. Mistarihi, and Ghazi M. Magableh, "Prioritization of Supply Chain Capabilities Using the FAHP Technique," *Sustainability*, vol. 15, no. 7, pp. 1-19, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[45] Vipul Jain et al., "Supplier Selection using Fuzzy AHP and TOPSIS: A Case Study in the Indian Automotive Industry," *Neural Computing and Applications*, vol. 29, no. 7, pp. 555-564, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[46] Yongbo Li, and K. Mathiyazhagan, "Application of DEMATEL Approach to Identify the Influential Indicators towards Sustainable Supply Chain Adoption in the Auto Components Manufacturing Sector," *Journal of Cleaner Production*, vol. 172, pp. 2931-2941, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[47] Rinu Sathyan et al., "Modelling the Drivers of Responsiveness of Automotive Supply Chain Using an Integrated Fuzzy DEMATEL-ISM Approach," *Journal of Global Operations and Strategic Sourcing*, vol. 17, no. 2, pp. 209-229, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[48] Mohammad Faisal Noor et al., "Challenges in Adopting Industry 4.0 for Indian Automobile Industries: A Key Experts' Perspective," *European Journal of Automated Systems*, vol. 57, no. 1, pp. 239-253, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[49] Z. Joorbonyan, and F.Z. Montazeri, "Analyzing Causal Relationships among Supplier Evaluation Criteria in the Automotive Industry using the Fuzzy DEMATEL Method," *Modern Research in Performance Evaluation*, vol. 4, no. 2, pp. 91-109, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[50] R.M. Zulqarnain et al., "Application of TOPSIS Method for Decision Making," *International Journal of Scientific Research in Mathematical and Statistical Sciences*, vol. 7, no. 2, pp. 76-81, 2020. [Google Scholar] [Publisher Link]

[51] Asis Sarkar, "A TOPSIS Method to Evaluate the Technologies," *International Journal of Quality & Reliability Management*, vol. 31, no. 1, pp. 2-13, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[52] Yuan Liang, "An EDAS Method for Multiple Attribute Group Decision-Making Under Intuitionistic Fuzzy Environment and Its Application for Evaluating Green Building Energy-Saving Design Projects," *Symmetry*, vol. 12, no. 3, pp. 1-12, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[53] Yuhan Huang, Rui Lin, and Xudong Chen, "An Enhancement EDAS Method Based on Prospect Theory," *Technological and Economic Development of Economy*, vol. 27, no. 5, pp. 1019-1038, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[54] Ashis Mitra, "Selection of Cotton Fabrics Using EDAS Method," *Journal of Natural Fibers*, vol. 19, no. 7, pp. 2706-2718, 2022. [CrossRef] [Google Scholar] [Publisher Link]