



An Integrated Triple-Uncertainty Hybrid MCDM Approach: Leveraging Fuzzy-BWM, Intuitionistic Fuzzy-DEMATEL, and Rough TOPSIS for Supplier Selection in the Automotive industry 5.0

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Abstract: This study develops an integrated multi-criteria decision-making framework for supplier selection in a digitally enabled and increasingly complex supply-chain environment. The framework combines Fuzzy Best-Worst Method (F-BWM), Intuitionistic Fuzzy DEMATEL (IF-DEMATEL), and Rough TOPSIS to incorporate expert preferences, interrelationships among evaluation criteria, and uncertainty in supplier performance assessment. Nineteen criteria covering human-centric, technological, resilience, economic, and environmental dimensions were evaluated and integrated into a final criterion-weighting structure. The results identified AI/ML Integration Maturity (TC2), Cyber-Physical Systems Security (TC4), and Financial Stability (EC2) as the three highest-weighted criteria. The resulting weights were applied in the Rough TOPSIS evaluation of ten supplier alternatives. Supplier 3 emerged as the preferred supplier, followed by Suppliers 1 and 8, while Suppliers 2, 6, and 9 occupied the lowest positions. Sensitivity and rank-correlation analyses showed that although some changes occurred among suppliers with relatively close performance, the first position of Supplier 3 remained unchanged. The findings demonstrate that the proposed integrated framework provides a structured and robust basis for supplier selection by combining expert judgement, criterion interrelationships, and uncertain performance information.

Keywords: Supplier Selection, Multi-Criteria Decision Making, Fuzzy-BWM, Intuitionistic Fuzzy DEMATEL (IF-DEMATEL), Rough TOPSIS; Automotive Industry, Sustainability, Industry 5.0.

INTRODUCTION

The automotive industry is undergoing significant transformation with the emergence of industry 5.0 paradigm, which emphasizes sustainability, human-machine synergy, and resilience. Instead of considering the supplier selection as purely a transactional activity, modern procurement requires a more strategic approach that aligns supplier decisions with long-term environmental, social, technological, and financial objectives (Luthra *et al.*, 2016). Selecting suitable suppliers has therefore become an important means of strengthening supply-chain sustainability, supporting innovation, and

enhancing the industry's ability to respond to changing conditions. Historically, the Multi-Criteria Decision-Making (MCDM) tools, which include the Best-Worst Method (BWM), Analytic Hierarchy Process (AHP), Techniques for Order Preference by Similarity of Idea Solution (TOPSIS), and Decision-Making Trial and Evaluation Laboratory (DEMATEL), among others, have taken center stage in the supply-chain decision-making process. These techniques enable the decision-makers to make comparisons amongst the suppliers on various aspects and make trade-offs. Nevertheless, they are often based on simplified assumptions that considers criteria independently, assumes expert judgments are supposed to be accurate, and that performance data are often deterministic (Yildiz and Yayla, 2015; Mugoni *et al.*, 2023). In practice, these assumptions are not generally true as factors such as cost, operations, technological, innovation and environmental impact tend to affect each other. More so, opinions of experts are usually ambiguous, and supplier performance may improve or decline with time.

Furthermore, the issue of sustainability also makes the situation more complicated. Current procurement decisions should not focus solely on economic efficiency, but should also consider incorporate social responsibility, technological preparedness and environmental stewardship (Sahu *et al.*, 2022). To resolve these dimensions under uncertainty, scholars have frequently resulted to the use of hybrid MCDM models (Gidiagba *et al.*, 2025). However, most of the available frameworks fail to reflect the complexity of uncertainty particularly when the decision-makers are required to deal with uncertainty around experts' judgement, and information that is not crisp-cut. Causal interdependencies among the evaluation criteria also represent a critical consideration. In the automotive industry, for example, a supplier's digital capability may enhance its environmental performance, which can subsequently influence its cost efficiency and delivery reliability. Ignoring these cause-and-effect relationships may lead to incorrect supplier-selection decisions, particularly in a rapidly changing environment. To address this gap, this study proposes an integrated hybrid framework that captures three forms of uncertainty in the supplier-selection process:

- (i) Fuzzy-BWM which represents linguistic vagueness in expert judgment.
- (ii) Intuitionistic Fuzzy DEMATEL (IF-DEMATEL) which capture hesitation and causality interrelationship among criteria and
- (iii) Rough TOPSIS which process rough or interval-based supplier performance data.

A combination of these methods enables the framework to deal with several levels of uncertainty and identify the interdependencies that define the contexts of decision-making in the industry 5.0 environment.

The framework is applied to a real-world situation to demonstrate its practical applicability. Ten automotive suppliers and nineteen criteria based on economic, human centricity, sustainability, environmental, and technological aspects will be analyzed.

MATERIALS AND METHODS

2.1 Research Design and Criteria Development

This study developed an integrated decision-making approach for evaluating suppliers in the automotive Industry 5.0 environment. The approach brings together the Fuzzy Best-Worst Method, Intuitionistic Fuzzy DEMATEL, and Rough TOPSIS. These methods tend to address three important aspects of supplier evaluation (uncertainty in expert judgement, relationships among evaluation criteria, and imprecision in supplier performance assessments) (Rezaei, 2016; Guo & Zhao, 2017; Si *et al.*, 2015). Ten automotive suppliers will be evaluated using nineteen criteria grouped into five dimensions namely, human-centric, technological, resilience, economic, and environmental considerations. The criteria were drawn from relevant research on supplier selection, sustainability, industrial decision-making, and Industry 5.0 (Govindan *et al.*, 2015; Si *et al.*, 2015; Breque *et al.*, 2021). The criteria are presented to twelve experienced professionals with backgrounds in automotive manufacturing, procurement, and supply chain management to determine the relevance of the criteria to the supplier evaluation context. This process resulted in the final set of nineteen criteria used in the analysis. The identities of the participating experts were kept confidential. Selection was based on their professional experience, managerial responsibilities, and direct involvement in supplier evaluation and

related decision-making activities. The validated criteria formed the basis for the weighting, interrelationship analysis, and supplier-ranking stages of the study.

2.2 Expert Evaluation and Fuzzy Best-Worst Method

The Fuzzy Best-Worst Method (F-BWM) is applied to determine the relative importance of the criteria. The method was selected because it reduces the number of pairwise comparisons required from experts while allowing uncertainty and vagueness in their judgements to be represented using fuzzy numbers (Rezaei, 2015; Guo and Zhao, 2017). Each expert first identified the best criterion, representing the criterion considered most important, and the worst criterion, representing the least important among the 19 criteria. The experts then assessed the preference of the best criterion over each of the remaining criteria and the preference of each criterion over the worst criterion. The judgements were expressed using the nine-point linguistic scale adopted in this study. The corresponding linguistic terms and triangular fuzzy number (TFN) representations are presented in Table-1.

Table-1 Linguistic Scale and Corresponding TFNs

Scale	Interpretation	TFN (l, m, u)
1	Equally Important	(1,1,1)
2	Slightly More Important	(1,2,3)
3	Weakly More Important	(2,3,4)
4	Moderately More Important	(3,4,5)
5	Strongly More Important	(4,5,6)
6	Very Strongly More Important	(5,6,7)
7	Extremely More Important	(6,7,8)
8	Very Extremely More Important	(7,8,9)
9	Absolutely More Important	(9,9,9)

The linguistic judgements were converted into triangular fuzzy numbers, expressed as:

$$\tilde{a}_{Bj} = (a_{Bj}^l, a_{Bj}^m, a_{Bj}^u) \quad (1)$$

For the Best-to-Others comparisons and

$$\tilde{a}_{jW} = (a_{jW}^l, a_{jW}^m, a_{jW}^u) \quad (2)$$

For the Others-to-Worst comparisons. The resulting fuzzy comparisons were aggregated across the expert panel and used as inputs to the F-BWM optimization model. Let the fuzzy weight of criterion j be represented by:

$$\tilde{\omega}_j = (\omega_j^l, \omega_j^m, \omega_j^u), \quad (3)$$

where ω_j^l , ω_j^m , and ω_j^u denote the lower, modal, and upper values of the fuzzy weight, respectively. The optimal fuzzy weights were obtained by minimising the maximum deviation between the weight ratios and the corresponding fuzzy comparison values:

$$\min \xi^* \quad (4)$$

subject to the Best-to-Others constraints:

$$\left| \frac{\omega_B^l}{\omega_j^l} - a_{Bj}^l \right| \leq k^*, \quad \left| \frac{\omega_B^m}{\omega_j^m} - a_{Bj}^m \right| \leq k^*, \quad \left| \frac{\omega_B^u}{\omega_j^u} - a_{Bj}^u \right| \leq k^* \quad (5)$$

and the Others-to-Worst constraints:

$$\left| \frac{\omega_j^l}{\omega_W^l} - a_{jW}^l \right| \leq k^*, \quad \left| \frac{\omega_j^m}{\omega_W^m} - a_{jW}^m \right| \leq k^*, \quad \left| \frac{\omega_j^u}{\omega_W^u} - a_{jW}^u \right| \leq k^* \quad (6)$$

The fuzzy weights were constrained to maintain their lower-to-upper ordering and satisfy the normalization condition:

$$\sum_{j=1}^n \omega_j^m = 1 \text{ and } \omega_j^l \leq \omega_j^m \leq \omega_j^u, \quad \omega_j^l \geq 0 \quad (7)$$

The resulting ω_j^{BMW} weights are the normalized original preference weights of all the final criteria.

2.3 Intuitionistic Fuzzy DEMATEL for Criteria Interrelationship Analysis

The Intuitionistic Fuzzy DEMATEL (IF-DEMATEL) method is applied to examine the interrelationships among the 19 supplier-selection criteria. While F-BWM determines the relative importance of the criteria based on expert preferences, IF-DEMATEL establishes the extent to which the criteria influence one another. The method is appropriate for this purpose because it represents uncertainty and hesitation in expert assessments of inter-criteria relationships (Xue and Deng, 2021; Liao et al., 2023). The experts assess the influence of each criterion on every other criterion using an intuitionistic fuzzy linguistic scale. Each judgement is represented by a membership degree μ , a non-membership degree ν , and a hesitation degree π , defined as:

$$\pi = 1 - \mu - \nu. \quad (8)$$

The individual expert assessments are then aggregated to construct the intuitionistic fuzzy direct-relation matrix:

$$\tilde{Z} = [\tilde{z}_{ij}]_{n \times n} \quad (9)$$

where $\tilde{z}_{ij}$ represents the influence of criterion i on criterion j . The resulting matrix is normalized before determining the total relationships among the criteria. The normalized direct-relation matrix is subsequently used to obtain the total-relation matrix, accounting for both direct and indirect influences among the 19 criteria. From this matrix, the total influence given and received by each criterion are calculated as:

$$DR_{i_i} = \sum_{j=1}^n t_{ij}, \quad (10)$$

$$R_i = \sum_{j=1}^n t_{ji}, \quad (11)$$

The prominence and net causal influence of each criterion are then determined as:

$$P_i = D_i + R_i, \quad (12)$$

$$C_i = D_i - R_i, \quad (13)$$

Here, P_i indicates the overall degree to which criterion i is involved in the system, while C_i indicates its net influence. Criteria with positive C_i values are regarded as causal or driving criteria, whereas those with negative values are regarded as effect or receiving criteria. The resulting structural information for the 19 criteria is subsequently combined with their corresponding F-BWM preference weights. This integration allows the final criterion weights to reflect both the perceived importance of each criterion and its structural position within the overall criteria system.

2.4 Integration of F-BWM Weights and IF-DEMATEL Structural Influence

The F-BWM weights represent the relative importance assigned to the 19 criteria by the expert panel, while IF-DEMATEL provides information on the structural influence of each criterion within the criteria system. The two outputs are therefore combined to obtain a final weight for each criterion. This integration ensures that the weighting process considers not only the perceived importance of a criterion but also its position and influence within the network of criteria.

Let ω_j denote the F-BWM weight of criterion j , and let s_j represent its corresponding structural influence obtained from IF-DEMATEL. The integrated weight of each criterion is determined by combining these two measures:

$$W_j = f(\omega_j, s_j) \quad (14)$$

where W_j represents the integrated weight of criterion j , ω_j is its F-BWM preference weight, and s_j is its structural influence obtained from IF-DEMATEL.

The resulting weights are then normalized so that the sum of the weights across the 19 criteria equals one:

$$W_j^* = \frac{W_j}{\sum_{j=1}^n W_j}, j = 1, 2, \dots, n \quad (15)$$

The normalized vector

$$W^* = (W_1^*, W_2^*, \dots, W_n^*) \quad (16)$$

Equation (11) provides the final criterion weights for the supplier evaluation stage. These weights are subsequently applied to the supplier performance data in the Rough TOPSIS procedure.

2.5 Rough TOPSIS for Supplier Evaluation and Ranking

The final criterion weights obtained from the integration of F-BWM and IF-DEMATEL are used in the Rough TOPSIS procedure to evaluate and rank the ten suppliers. Rough TOPSIS is adopted to retain the uncertainty and variation associated with supplier performance assessments rather than representing each assessment by a single crisp value (Wang and Chen, 2008; Greco *et al.*, 2001).

Supplier performance is assessed against the 19 criteria, producing the initial decision matrix:

$$X = [x_{ij}]_{m \times n} \quad (17)$$

where x_{ij} represents the performance of supplier i with respect to criterion j .

The performance assessments are converted into rough numbers using lower and upper approximations. Thus, each supplier-criterion assessment is represented as:

$$\tilde{x}_{ij} = [\underline{x}_{ij} \bar{x}_{ji}] \quad (18)$$

where $\underline{x}_{ij}$ and $\bar{x}_{ji}$ represent the lower and upper approximations of the performance of supplier i on criterion j . The use of rough values helps retain the variation in the assessments provided by the evaluators during the ranking process. The rough decision matrix is then normalized to place the performance values on a common scale across the 19 criteria. The normalization procedure takes into account the type of criterion, with higher values preferred for benefit criteria and lower values preferred for cost criteria. The normalized rough values are subsequently combined with the final criterion weights to obtain the weighted rough decision matrix:

$$\tilde{V} = [\tilde{v}_{ij}] \quad (19)$$

Where

$$\tilde{v}_{ij} = \tilde{r}_{ij} W_j^*, \quad (20)$$

with $\tilde{r}_{ij}$ representing the normalized rough performance of supplier i on criterion j , and W_j^* representing the final weight of criterion j . The positive ideal solution A^+ and negative ideal solution A^- are then determined from the weighted rough decision matrix. The positive ideal solution represents the most desirable performance across the criteria, whereas the negative ideal solution represents the least desirable performance. The distance of each supplier from the two ideal solutions is calculated using the Euclidean distance measure for rough numbers. These distances are denoted by D_i^+ and D_i^- representing the distance from the positive and negative ideal solutions, respectively. The relative closeness coefficient of each supplier is then calculated as:

$$CC_i = \frac{D_i^-}{D_i^+ - D_i^-} \quad (21)$$

A higher value of CC_i indicates that a supplier is closer to the positive ideal solution and farther from the negative ideal solution. The suppliers are therefore ranked in descending order of their closeness coefficients, with the supplier having the highest CC_i receiving the highest rank. This procedure provides the final supplier ranking based on the 19 criteria, their integrated weights, and the assessed supplier performance.

RESULTS AND DISCUSSION

This section presents and discusses the results obtained from the hybrid Fuzzy-BWM, IF-DEMATEL, and Rough TOPSIS framework. The results are examined in terms of the importance of the 19 criteria, their interrelationships, and the resulting supplier rankings. The discussion focuses on what these findings mean for sustainable supplier selection in the automotive Industry 5.0 context, rather than simply reporting the numerical results.

3.1 Criteria Weighting Analysis (Fuzzy-BWM)

The F-BWM results provide the relative importance assigned to the 19 criteria by the expert panel. As presented in Table-2, the criterion weights range from 0.031337 to 0.072354, indicating noticeable differences in the perceived importance of the criteria within the supplier evaluation framework. The results demonstrate that RC3 received the highest weight (0.072354), followed by EC2 (0.069722), TC2 (0.069029), and TC4 (0.068645). These criteria therefore occupy the most prominent positions in the initial preference structure established by the experts. The relatively high weight assigned to RC3 suggests that this criterion is particularly important to supplier selection under the conditions

considered in the study. EC2, TC2, and TC4 also received weights close to that of RC3, indicating that the experts did not view supplier performance from a single perspective. Rather, the results point to a combination of resilience, economic, and technological considerations as important elements of supplier evaluation. This is consistent with the broader argument that supplier selection in contemporary manufacturing environments requires consideration of multiple and sometimes competing requirements rather than reliance on conventional cost-based measures alone.

The middle portion of the ranking is occupied by SC4 (0.062818), EN3 (0.061448), TC1 (0.058602), EN2 (0.057535), RC2 (0.055374), and SC2 (0.053492). Although these criteria do not occupy the four highest positions, their weights remain substantial. In particular, the relatively close weights across these criteria suggest that the experts considered several aspects of supplier capability to be important rather than assigning overwhelming importance to only a small number of factors.

Table-2 F-BWM weights and ranking of the 19 supplier-selection criteria

Rank	Dimension	Abbreviation	Sub-Criterion	Crisp Weight
1	Resilience	RC3	Risk Management Maturity Level	0.072354
2	Economic	EC2	Financial Stability	0.069722
3	Technological	TC2	AI/ML Integration Maturity	0.069029
4	Technological	TC4	Cyber-Physical Systems (CPS) Security	0.068645
5	Sustainability	SC4	Well-being and Ergonomics Score	0.062818
6	Environmental	EN3	Waste Reduction & Recycling Rate	0.061448
7	Technological	TC1	Digital Twin Data Readiness	0.058602
8	Environmental	EN2	Energy Consumption Efficiency	0.057535
9	Resilience	RC2	Supply Chain Visibility and Transparency	0.055374
10	Sustainability	SC2	Ethical AI Governance Framework	0.053492
11	Economic	EC1	Life Cycle Cost (LCC) Analysis Maturity	0.048337
12	Economic	EC3	Cost of Quality (CoQ) Performance	0.047942
13	Resilience	RC4	Agility in Volume Fluctuation	0.044895
14	Environmental	EN1	Circular Economy Compliance Index	0.043404
15	Resilience	RC1	Supply Chain Network Redundancy	0.041645
16	Sustainability	SC1	Human-Machine Augmentation Index	0.039655
17	Technological	TC3	Real-Time Data Sharing Protocols	0.036972
18	Sustainability	SC3	Continuous Training & Skill Adaptability	0.036793
19	Economic	EC4	Dynamic Pricing Flexibility	0.031337

At the lower end of the ranking, EC4 recorded the smallest weight (0.031337), followed by SC3 (0.036793), TC3 (0.036972), SC1 (0.039655), and RC1 (0.041645) as presented in Fig.1.

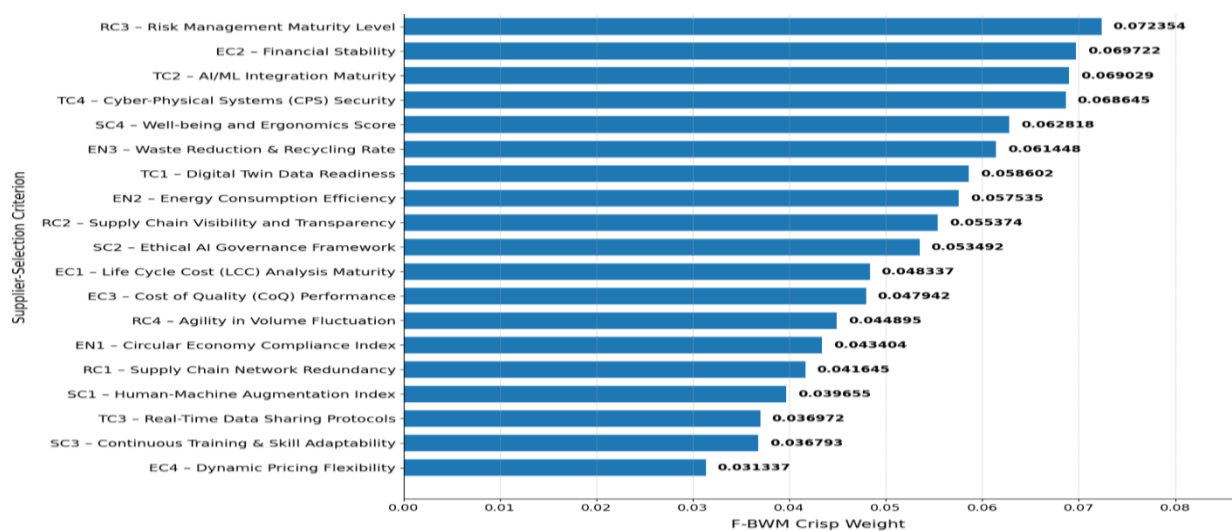


Fig. 1 Fuzzy-BWM criteria weights

A lower F-BWM weight does not mean that a criterion is unimportant. It simply means that the experts considered it less important compared with the other criteria. This distinction is important because all 19 criteria remain part of the subsequent supplier evaluation. Overall, the F-BWM results establish the baseline preference structure for the study. The ranking indicates that supplier evaluation is influenced by a combination of resilience, economic, technological, sustainability, and environmental considerations. However, these weights capture the experts' assessment of relative importance and do not, by themselves, indicate how the criteria interact with one another.

3.2 IF-DEMATEL

The IF-DEMATEL analysis was used to examine the relationships among the 19 supplier-selection criteria. The analysis considers not only the influence that each criterion exerts on the others but also the influence it receives from them. This provides a clearer understanding of the position of each criterion within the overall decision system. Based on the aggregated assessments of the twelve experts, the total-relation matrix was obtained and used to calculate the total influence given (D_i), total influence received (R_i) prominence ($D_i + R_i$), and net influence ($D_i - R_i$) for each criterion. The prominence results as illustrated in Table 3 and Figure 2, indicate that TC4, TC3, TC2, and RC4 occupy the most highly connected positions within the system. TC4 records the highest prominence value (5.809622), followed closely by TC3 (5.809225) and TC2 (5.787172). This finding suggests that these technological criteria have strong overall interactions with the remaining criteria and play an important role in the structure of the evaluation system. The causal results as presented in Fig. 3, provide further insight into the direction of these relationships. TC1 records the highest positive net influence value (1.350492), followed by TC2 (1.293639), RC3 (1.260213), RC2 (1.231381), RC1 (1.064509), TC3 (1.030776), TC4 (0.845193), and RC4 (0.460315).

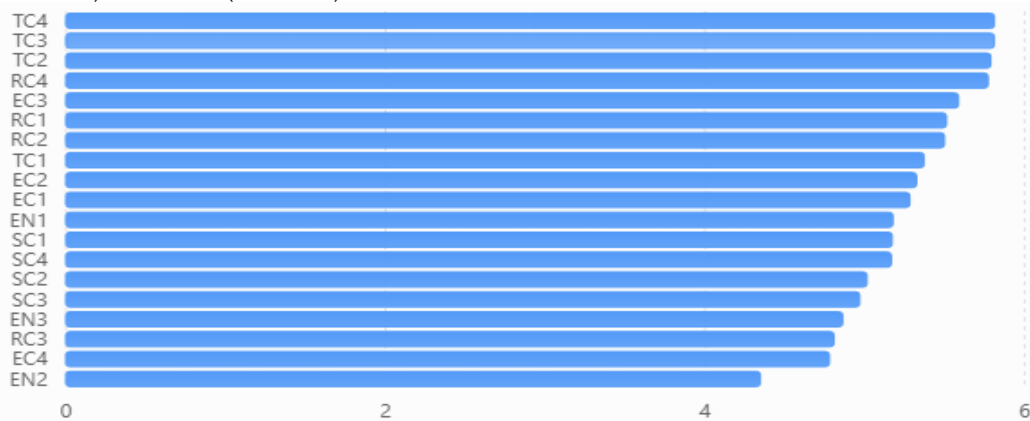


Fig. 2 IF-DEMATEL Prominence of the 19 Criteria

These criteria belong to the cause group because they exert greater influence on the other criteria than they receive from them. Their position in the cause group indicates that changes in these criteria may generate effects across other areas of the supplier-evaluation system. In contrast, SC1 records the most negative net influence value (−1.151575), followed by EC1 (−1.037836), EC2 (−1.029586), EC3 (−0.998286), and SC3 (−0.980830). These criteria belong to the effect group, meaning that they receive greater influence from the other criteria than they exert. Their position suggests that their performance may be shaped by changes occurring in the technological, resilience, and other causal criteria. A comparison of the F-BWM and IF-DEMATEL results reveals that criterion importance and structural influence do not necessarily produce the same ranking. For instance, RC3 receives the highest F-BWM weight (0.072354), although its prominence value in the IF-DEMATEL analysis is comparatively lower (4.806304). Conversely, TC1 has a lower F-BWM weight (0.058602) but records the highest positive net influence (1.350492). This difference demonstrates the complementary nature of the two methods. F-BWM reflects the experts' perceived importance of each criterion, whereas IF-DEMATEL demonstrates how strongly each criterion interacts with and influences the others within the system.

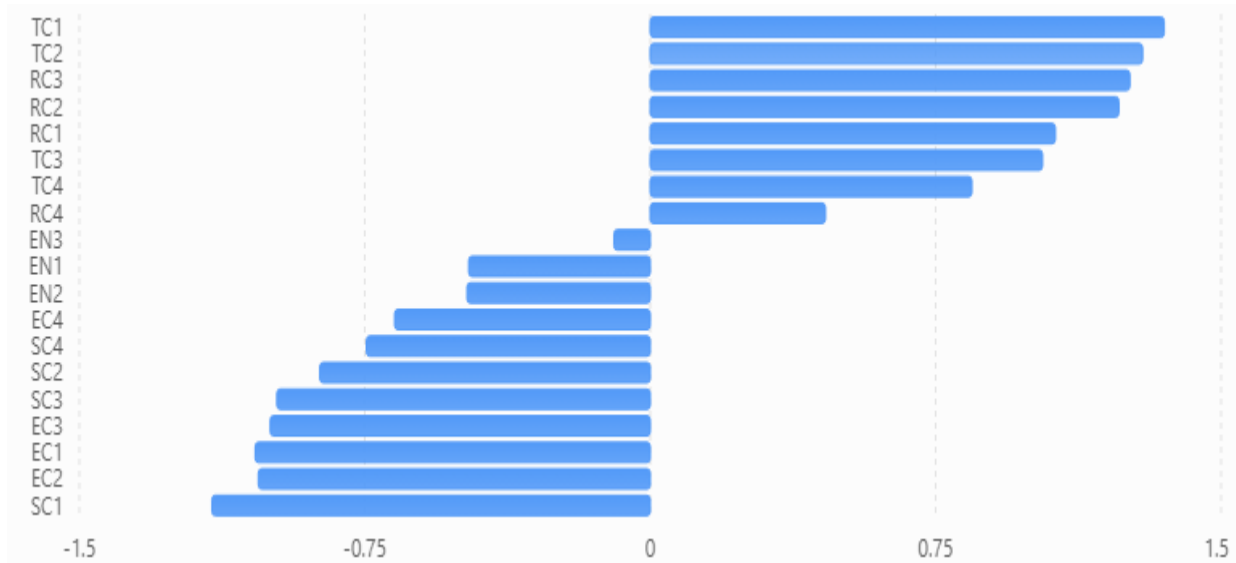


Fig. 3 IF-DEMATEL Net Causal Influence of the 19 Criteria

Table-3 IF-DEMATEL Prominence and Causal Influence

Rank	Criterion	D_i	R_i	$D_i + R_i$	$D_i - R_i$	Classification
1	TC4	3.327408	2.482214	5.809622	0.845193	Cause
2	TC3	3.420001	2.389225	5.809225	1.030776	Cause
3	TC2	3.540406	2.246766	5.787172	1.293639	Cause
4	RC4	3.115478	2.655163	5.770641	0.460315	Cause
5	EC3	2.293401	3.291688	5.585089	-0.998286	Effect
6	RC1	3.286999	2.222490	5.509488	1.064509	Cause
7	RC2	3.364366	2.132985	5.497352	1.231381	Cause
8	TC1	3.360351	2.009859	5.370210	1.350492	Cause
9	EC2	2.146568	3.176154	5.322723	-1.029586	Effect
10	EC1	2.121251	3.159086	5.280337	-1.037836	Effect
11	EN1	2.348951	2.825809	5.174761	-0.476858	Effect
12	SC1	2.009148	3.160722	5.169870	-1.151575	Effect
13	SC4	2.209444	2.955014	5.164458	-0.745570	Effect
14	SC2	2.072069	2.940050	5.012119	-0.867980	Effect
15	SC3	1.992922	2.973752	4.966673	-0.980830	Effect
16	EN3	2.382404	2.477648	4.860052	-0.095244	Effect
17	RC3	3.033259	1.773046	4.806304	1.260213	Cause
18	EC4	2.052633	2.724125	4.776758	-0.671491	Effect
19	EN2	1.931901	2.413163	4.345064	-0.481262	Effect

Accordingly, a criterion may be considered highly important by the experts without being a major driver of the system, while another criterion may have a relatively lower direct weight but exert substantial influence on other criteria. These findings justify the integration of the two methods. The F-BWM weights capture preference-based importance, while the IF-DEMATEL results contribute information about interrelationships and causal influence. Together, they provide a more comprehensive basis for deriving the integrated criterion weights used in the next stage of the analysis.

3.3 Integration of F-BWM Weights and IF-DEMATEL Structural Influence

The F-BWM and IF-DEMATEL analyses provide complementary information about the 19 supplier-selection criteria. The F-BWM results reflect the relative importance assigned by the experts, while the IF-DEMATEL results indicate the structural prominence of each criterion within the criteria system. These two results were therefore combined to obtain the integrated criterion weights used in the supplier evaluation as illustrated in Table-4.

Table-4 Integrated F-BWM-IF-DEMATEL Weights

Rank	Criterion	F-BWM Weight	IF-DEMATEL Prominence	Normalized Prominence	Integrated Weight
1	TC2	0.069029	5.787172	0.057861	0.075864
2	TC4	0.068645	5.809622	0.058086	0.075735
3	EC2	0.069722	5.322723	0.053218	0.070476
4	RC3	0.072354	4.806304	0.048054	0.066041
5	SC4	0.062818	5.164458	0.051635	0.061609
6	TC1	0.058602	5.370210	0.053692	0.059764
7	RC2	0.055374	5.497352	0.054964	0.057809
8	EN3	0.061448	4.860052	0.048592	0.056714
9	SC2	0.053492	5.012119	0.050112	0.050915
10	EC3	0.047942	5.585089	0.055841	0.050849
11	RC4	0.044895	5.770641	0.057696	0.049199
12	EC1	0.048337	5.280337	0.052794	0.048471
13	EN2	0.057535	4.345064	0.043443	0.047475
14	RC1	0.041645	5.509488	0.055085	0.043573
15	EN1	0.043404	5.174761	0.051738	0.042654
16	TC3	0.036972	5.809225	0.058082	0.040788
17	SC1	0.039655	5.169870	0.051689	0.038933
18	SC3	0.036793	4.966673	0.049658	0.034703
19	EC4	0.031337	4.776758	0.047759	0.028427

The integrated weighting results as presented in Fig. 4, indicates that TC2 (AI/ML Integration Maturity) has the highest overall weight (0.075864), followed closely by TC4 (CPS Security), with a weight of 0.075735. EC2 (Financial Stability) ranks third, with an integrated weight of 0.070476. The high positions of these criteria indicate that they combine relatively strong expert preference with a significant structural role within the criteria system. A notable change occurred in the position of RC3 (Risk Management Maturity Level). Although RC3 received the highest F-BWM weight (0.072354), it dropped to fourth place after the integration process, with a final weight of 0.066041.

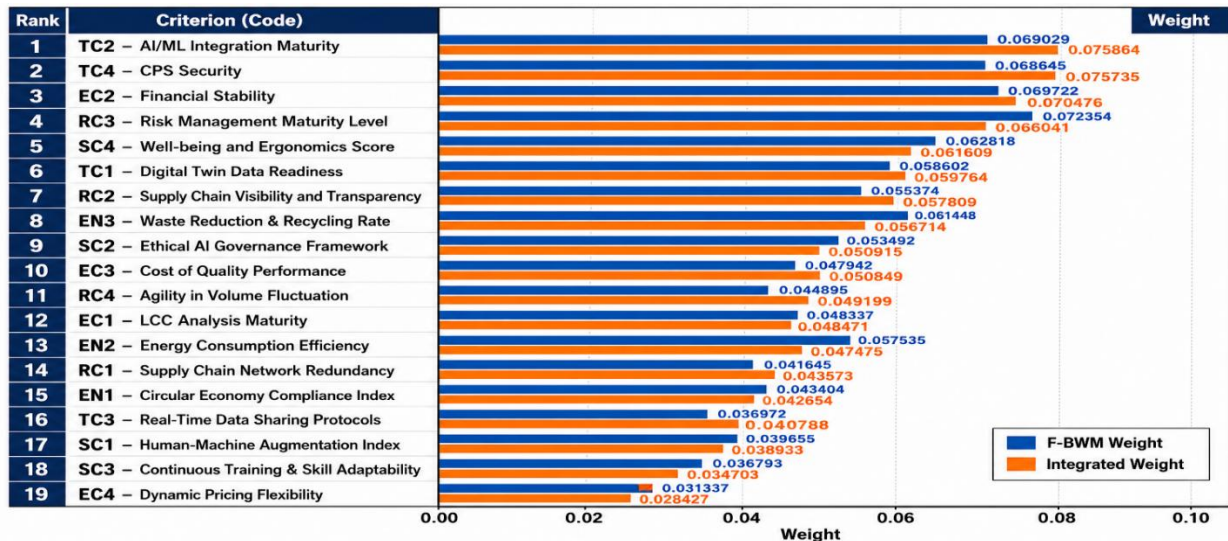


Fig. 4 Comparison of F-BWM and Integrated Criterion Weights

This change is associated with its comparatively lower IF-DEMATEL prominence value of 4.806304. The result demonstrates that a criterion with a high preference weight may not necessarily receive the highest integrated weight when its structural position within the system is also taken into account. A similar pattern is observed for TC3 (Real-Time Data Sharing Protocols) that had relatively low (0.036972) F-BWM weight but recorded a very high IF-DEMATEL prominence value of 5.809225. As a result, its integrated weight increased to 0.040788. This finding illustrates how structural information can strengthen the position of a criterion that may receive comparatively less direct preference from the experts. In general, the integrated results confirm that expert preference and structural prominence do not always produce the same ranking of criteria. The combined weighting approach therefore provides

a broader representation of criterion importance by considering both the experts' direct assessments and the relationships among the criteria. The resulting integrated weights are subsequently used in the Rough TOPSIS analysis to rank the ten suppliers.

3.4 Rough TOPSIS Supplier Ranking

The integrated criterion weights obtained from the F-BWM and IF-DEMATEL analysis were applied to the rough supplier-performance assessments to determine the final ranking of the ten suppliers. The Rough TOPSIS analysis considers the uncertainty retained in the expert assessments while incorporating the relative importance of the 19 criteria. The resulting distances from the positive and negative ideal solutions, together with the corresponding closeness coefficients, are presented in Table-5

Table-5 Rough TOPSIS Supplier Ranking

Rank	Supplier	Distance from Positive Ideal (D_i^+)	Distance from Negative Ideal (D_i^-)	Closeness (CC_i)	Coefficient
1	Supplier 3	0.029307	0.165591	0.849628	
2	Supplier 1	0.051934	0.148428	0.740798	
3	Supplier 8	0.052651	0.145967	0.734912	
4	Supplier 10	0.061744	0.134523	0.685410	
5	Supplier 5	0.064165	0.135395	0.678470	
6	Supplier 4	0.075760	0.124139	0.621009	
7	Supplier 7	0.085190	0.110797	0.565329	
8	Supplier 2	0.119339	0.077676	0.394266	
9	Supplier 6	0.135667	0.068723	0.336234	
10	Supplier 9	0.155488	0.048112	0.236305	

The results reveal clear differences in the overall performance of the ten suppliers. Supplier 3 emerges as the best-performing alternative, with a closeness coefficient of 0.849628. Its distance from the positive ideal solution is only 0.029307, whereas its distance from the negative ideal solution is 0.165591. This indicates that Supplier 3 performs substantially closer to the desired supplier profile than to the least desirable profile across the evaluation criteria. Supplier 1 and Supplier 8 occupy the next two positions, with closeness coefficients of 0.740798 and 0.734912, respectively. The small difference between their coefficients suggests that their overall performance levels are relatively similar. Both suppliers are considerably closer to the positive ideal than to the negative ideal, although neither achieved the performance level recorded by Supplier 3.

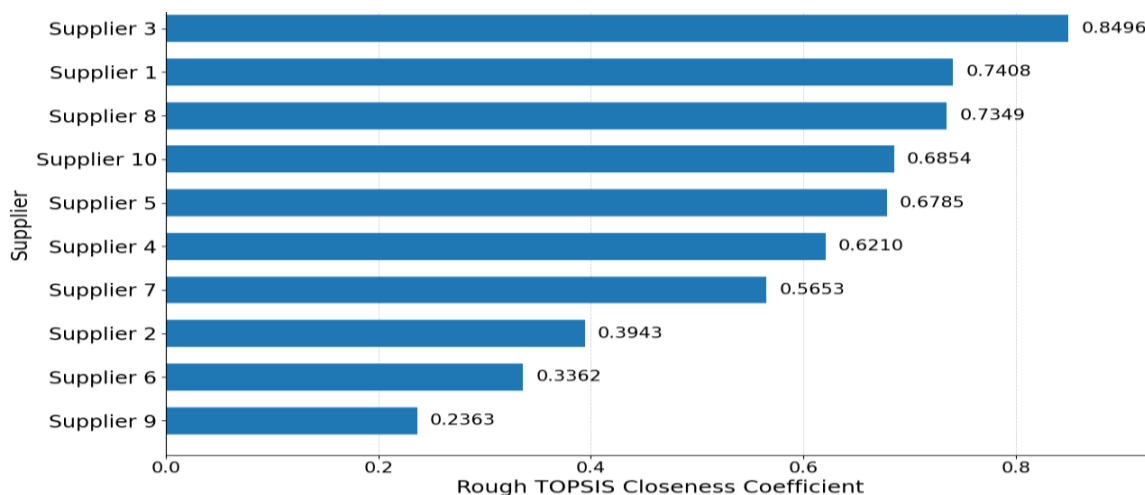


Fig.5 Rough TOPSIS Supplier Ranking

A second performance group appears in the middle of the ranking. Supplier 10 and Supplier 5 record closeness coefficients of 0.685410 and 0.678470, respectively, followed by Supplier 4 with a coefficient of 0.621009. These suppliers demonstrate reasonably strong overall performance, but their greater distances from the positive ideal solution place them below the leading alternatives. Supplier 7, with a closeness coefficient of 0.565329, occupies seventh position and is positioned near the middle of the

overall ranking. The lower end of the ranking reflects a more pronounced performance gap. Supplier 2 records a closeness coefficient of 0.394266, while Supplier 6 obtains 0.336234 as illustrated in Fig. 5. Compared with the higher-ranked suppliers, both alternatives are relatively farther from the positive ideal solution. Supplier 9 records the weakest overall performance, with a closeness coefficient of only 0.236305. Its distance from the positive ideal solution is the largest among all ten suppliers (0.155488), while its distance from the negative ideal solution is the smallest (0.048112). These values clearly explain its last position in the ranking. Taken together, the results indicate that the suppliers do not perform uniformly across the 19 evaluation criteria. Each supplier's position reflects the combined effect of its assessed performance, the relative importance of the criteria, and the structural information incorporated through the F-BWM-IF-DEMATEL weighting process. Supplier 3's leading position therefore reflects its stronger overall fit with the desired supplier profile rather than superiority in only one criterion.

The results also demonstrate the value of the Rough TOPSIS approach for supplier evaluation under uncertainty. Instead of representing supplier assessments as completely precise values, the rough-number formulation accommodates differences and imprecision in the experts' evaluations during the ranking process. This makes the resulting ordering more suitable for the uncertain and complex decision environment associated with Industry 5.0 automotive supply chains. Overall, Supplier 3 is identified as the preferred supplier, followed by Supplier 1 and Supplier 8. Suppliers 6 and 9 occupy the lowest positions in the ranking. These results provide a basis for further examining the strengths and weaknesses of each alternative and, where appropriate, testing the stability of the ranking under different weighting schemes or assessment conditions.

3.5 Robustness and Sensitivity Analysis

The robustness of the supplier ranking was examined from three complementary perspectives. First, the proposed integrated weighting scheme was compared with alternative ways of representing criterion importance. Second, the resulting supplier rankings were compared statistically using Spearman's rank correlation coefficient. Finally, a critical-weight analysis was considered to determine how much change in criterion importance would be required before the leading supplier loses its first position.

3.5.1 Comparison of Alternative Weighting Schemes

The proposed F-BWM-IF-DEMATEL method combines two types of information. The experts' preference weights and the structural prominence of the criteria within the decision system. To examine whether the supplier ranking depends strongly on this particular weighting formulation, the Rough TOPSIS analysis was then considered under alternative weighting schemes.

Table-6 Supplier Rankings under Alternative Weighting Schemes

Rank	Baseline	F-BWM Only	IF-DEMATEL Only	Proposed Multiplicative Integration	Arithmetic Integration
1	S3	S3	S3	S3	S3
2	S1	S5	S8	S8	S8
3	S8	S8	S1	S1	S1
4	S10	S1	S5	S5	S5
5	S5	S10	S10	S10	S10
6	S4	S4	S4	S4	S4
7	S7	S7	S7	S7	S7
8	S2	S2	S2	S2	S2
9	S6	S9	S9	S9	S9
10	S9	S6	S6	S6	S6

The most notable feature of Table-6 is the consistency of Supplier 3 that occupied the first position under every weighting configuration examined. Supplier 3 maintains the strongest overall performance across all ten alternatives under each weighting configuration, regardless of whether the criterion weights reflect expert preference, structural prominence, or a combination of both as illustrated in Figure 6. This provides an initial indication that its leading position is not simply a result of the particular weighting formulation used in the study. The comparison becomes more interesting among

suppliers whose overall performances are relatively close. This is particularly evident in the positions of Suppliers 1 and 8. Supplier 1 ranks second under the baseline weighting scheme, while Supplier 8 takes the second position when the alternative weighting configurations are applied. This small shift shows that the relative positions of these two suppliers are influenced by the way importance is assigned to the evaluation criteria. A similar pattern can be observed for Suppliers 5 and 10. Their positions change when the F-BWM weights are used independently, suggesting that the structural information provided by IF-DEMATEL contributes to the distinction between these closely ranked suppliers.

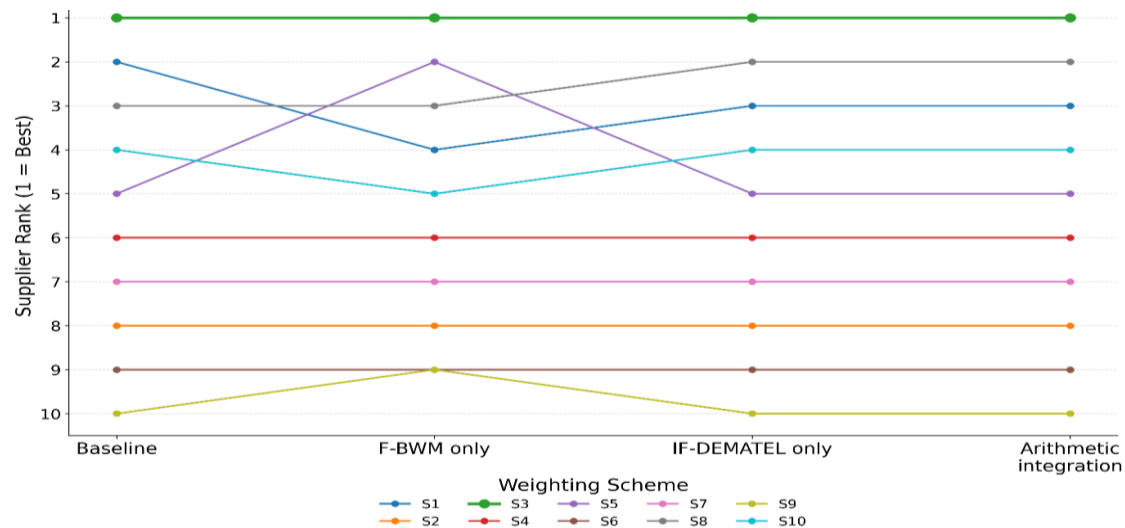


Fig. 6 Supplier Ranking Stability Across Alternative Weighting Schemes

There is also a small change at the bottom of the ranking. Under the F-BWM-only configuration, Supplier 6 moves below Supplier 9, whereas the baseline and other weighting approaches retain Supplier 6 in ninth position and Supplier 9 in tenth. This suggests that the distinction between these two suppliers is more sensitive to the weighting structure than the distinction between the leading alternatives and the weaker performers. Several positions, on the other hand, remain completely unchanged with Suppliers 3, 4, 7, and 2 retaining the same positions across all the weighting configurations. This consistency, together with the unchanged first position of Supplier 3, points to a relatively stable overall ranking despite the different ways in which criterion importance is represented. The comparison also highlights an important feature of the proposed integration. The purpose of combining F-BWM and IF-DEMATEL is not necessarily to produce a completely different supplier ranking. Rather, the integration allows the ranking to reflect both what experts consider important and how the criteria are structurally connected within the decision system.

3.5.2 Rank-Correlation Analysis

The ranking differences observed under the alternative weighting schemes were further examined using Spearman's rank correlation coefficient to determine whether these changes materially affect the overall supplier ordering. The results are presented in Table-7. The baseline records a correlation of 1.0000, as it serves as the reference ranking against which the other weighting configurations are compared. The alternative approaches all produce high correlation values, ranging from 0.9030 to 0.9636, which indicates that their supplier rankings remain closely aligned with the proposed model.

Table-7 Spearman Rank Correlation with the Baseline Ranking

Weighting Scheme	Spearman's (ρ)	Degree of Agreement
Baseline: Proposed F-BWM-IF-DEMATEL integration	1.0000	Perfect agreement
F-BWM only	0.9030	Very strong agreement
IF-DEMATEL prominence only	0.9636	Very strong agreement
Arithmetic integration	0.9636	Very strong agreement

The F-BWM-only approach has the lowest correlation ($\rho=0.9030$). This is consistent with the larger number of ranking changes observed in Table 6, where Suppliers 1, 5, 10, 6, and 9 experience positional changes relative to the baseline. In contrast, the IF-DEMATEL-only and arithmetic integration approaches both produce a correlation of 0.9636. Their rankings differ from the baseline mainly through the exchange of positions between Suppliers 1 and 8, while the positions of the other suppliers remain largely unchanged. The high correlation values therefore show that these positional changes do not substantially alter the overall structure of the supplier ranking. The different weighting approaches produce broadly similar ordering patterns, even though some individual suppliers respond differently to the way criterion importance is represented. Overall, the correlation analysis provides quantitative support for the robustness observed in the ranking comparison. It also indicates that the proposed integrated weighting approach does not produce a ranking that is substantially different from the alternative approaches. The main ranking pattern remains stable, while the differences are concentrated among suppliers with relatively close overall performance.

CONCLUSION

This study developed an integrated multi-criteria framework for supplier selection by combining F-BWM, IF-DEMATEL, and Rough TOPSIS. The framework incorporated expert preferences, relationships among the evaluation criteria, and supplier performance across the 19 selected criteria. The integrated weighting results identified TC2 (AI/ML Integration Maturity), TC4 (Cyber-Physical Systems Security), and EC2 (Financial Stability) as the highest-ranked criteria. The subsequent Rough TOPSIS evaluation ranked Supplier 3 as the best-performing alternative, followed by Suppliers 1 and 8. The sensitivity and rank-correlation analyses further showed that changes in the weighting structure affected some supplier positions but did not change Supplier 3's first position. This provides evidence that the main supplier-selection outcome is reasonably stable under the weighting conditions examined. Overall, the study demonstrates that combining expert preference, criterion interrelationships, and uncertain supplier-performance information can provide a more comprehensive basis for supplier selection. The framework also provides a foundation for future development towards adaptive and digitally enabled supplier-selection systems.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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