A Hybrid AI-MCDM Framework for Explainable Supplier Selection: A case study in the oil and gas sector

P.Sai Kiran[1], M.Srinivasa Rao[2]
[1]M. TECH (final year), Dept. of Mechanical, Sanketika Vidya Parishad Engineering College, Vizag, A.P, India
[2]Assiant Professor, Dept. of Mechanical, Sanketika Vidya Parishad Engineering College, Vizag, A.P, India

***Abstract*—Supplier selection is a strategic function in procurement, directly influencing cost,quality, and operational efficiency. Traditional Multi-Criteria Decision-Making (MCDM)methods such as AHP and TOPSIS provide transparency but struggle with large-scale, data-rich environments. Meanwhile, Machine Learning (ML) offers predictive power but often lacks interpretability. To address this gap, we propose two hybrid frameworks that integrate interpretable ML with MCDM. The first combines Decision Trees (DT) with AHP to reduce selection complexity and enhance ranking transparency. The second integrates FUCOM and TOPSIS with a DT classifier for improved adaptability. Using real datasets from the oil and gas sector, the DT+AHP model achieved up to 90% precision, while FUCOM+TOPSIS+DT improved F1-score by 5% compared to standalone ML models. The results demonstrate that hybrid approaches balance accuracy with explainability, making supplier decisions both data-driven and transparent. These findings highlight the potential of hybrid AI– MCDM systems for procurement in dynamic industrial environments.**

***Index Terms*—Supplier Selection, Hybrid AI–MCDM, Decision Tree, AHP, FUCOM, TOPSIS, Procurement**

I. INTRODUCTION

Problem Definition: Supplier selection is a critical strategic function in the oil and gas sector, where procurement decisions directly influence operational efficiency, project timelines, and overall cost performance. Unlike conventional industries, oil and gas procurement is characterized by:

1.High capital intensity – equipment, drilling operations, and maintenance contracts involve multi-million-dollar investments.

2.Complex supply chains – suppliers span multiple countries and tiers, often exposed to geopolitical and logistical risks.

3.Stringent quality and safety requirements – defects or delays can lead not only to financial loss but also to environmental hazards and safety incidents.

4.Dynamic market conditions – fluctuating oil prices, regulatory pressures, and sustainability mandates continuously reshape procurement priorities.

Traditional supplier evaluation approaches, such as manual scoring or standalone MCDM techniques, provide transparency but lack scalability and adaptability in such data-rich environments. Conversely, Machine Learning (ML) offers predictive power and automation but is often criticized for its "black-box" nature, which undermines stakeholder trust in high-stakes decisions.

Gap in Literature:

Extensive research has been conducted on supplier selection using both Multi-Criteria Decision-Making (MCDM) methods and Machine Learning (ML) approaches. However, both streams of research face significant limitations:

1.MCDM approaches (e.g., AHP, TOPSIS, FUCOM):

1.Strength: Provide structured, transparent, and explainable decision processes.

2.Limitation: Require extensive manual input and pairwise comparisons, which are impractical in large, data-rich procurement settings.

3.Weak adaptability: Static weighting schemes struggle to reflect dynamic market conditions or evolving supplier risks.

2.Machine Learning approaches (e.g., Decision Trees, SVM, ANN):

1.Strength: Deliver high predictive accuracy, handle complex, nonlinear data, and scale to large datasets.

2.Limitation: Many ML models function **as** "black boxes," offering limited interpretability for procurement managers.

3.Weak trust: Lack of explainability reduces stakeholder confidence in high-stakes domains like oil and gas procurement.
Contributions:
1.Development of Two Hybrid Frameworks:
1.DT + AHP Model – integrates a Decision Tree (DT) for reducing supplier selection complexity with the Analytic Hierarchy Process (AHP) for transparent ranking.
2.FUCOM + TOPSIS + DT Model – combines FUCOM for consistent criteria weighting, TOPSIS for ranking, and a DT classifier to enhance adaptability and predictive performance.
2. Case Study Validation in the Oil and Gas Sector:
1.Applied both frameworks to two large real-world procurement datasets covering cost, quality, delivery, risk, and sustainability criteria.
2.Demonstrated robustness of the models in a complex, high-stakes industry where procurement accuracy and transparency are equally critical.
3. Performance Improvements Over Baselines:
1.The DT + AHP model achieved up to 90% precision, outperforming standalone ML models.
2.The FUCOM + TOPSIS + DT model delivered an F1 score of 72.57%, representing a 5% performance gain compared to ML-only methods.
4.Advancing Explainable AI in Procurement:
1.By combining interpretable ML with MCDM, the proposed frameworks provide a balance between accuracy and transparency, ensuring procurement managers can both trust and understand model outcomes.
2.This dual emphasis enhances the practical adoption of AI-driven decision-support tools in supply chain management.

II. PROPOSED HYBRID FRAMEWORKS FOR SUPPLIER SELECTION

Step 1: Data Collection
The process begins with the acquisition of supplier-related data from procurement systems, enterprise resource planning (ERP) platforms, and external industry sources. In the oil and gas sector, such data typically includes:
1.Quantitative metrics such as purchase price, delivery lead times, defect counts, and financial ratios.
2.Qualitative attributes such as vendor certifications, compliance with industry standards, safety records, and sustainability practices.
3. Contextual factors such as geopolitical risk, regulatory changes, and supplier location-specific challenges.
Collecting comprehensive data is critical for ensuring that the model captures the multi-dimensional nature of supplier performance. Incomplete or biased datasets can result in rankings that misrepresent true supplier capabilities.
Step 2: Preprocessing
Procurement datasets are often heterogeneous, containing numerical, categorical, and textual information. Before analysis, the data must be preprocessed to improve consistency and reduce noise. Key preprocessing steps include:
1. Data Cleaning:
1.Handling missing values by applying imputation techniques (mean, median, or nearest neighbor imputation).
2.Removing duplicate or redundant records.
3.Addressing inconsistencies in supplier names, units of measurement, and currency conversions.
2. Data Transformation:
1.Normalizing numerical attributes (e.g., cost, defect rate) to a uniform scale to prevent bias during criteria weighting.
2.Encoding categorical variables (e.g., compliance levels, risk categories) into machine-readable formats.
3. Feature Reduction:
1.Eliminating irrelevant features to reduce computational overhead and prevent overfitting in the machine learning model.
2.Applying dimensionality reduction techniques (e.g., PCA, mutual information filtering) when datasets are high-dimensional.
4. Balancing the Dataset:
1.Ensuring class balance in classification problems (e.g., approved vs. rejected suppliers).
2.Oversampling minority classes or undersampling majority classes to avoid bias in the Decision Tree classifier.
Through preprocessing, the raw data is transformed into a clean, standardized dataset that is suitable for machine learning modeling and MCDM analysis.
Step 3: Decision Tree (DT) and Feature Engineering
At this stage, machine learning contributes interpretability and structure. Decision Trees (DT) are particularly advantageous because:
1.They naturally support feature selection,

highlighting which supplier attributes most influence performance.

2.Their rules can be expressed in if–then statements, making them more transparent compared to opaque models such as neural networks.

3.They facilitate scenario analysis, allowing managers to test "what-if" conditions (e.g., how rankings change if cost is weighted more heavily than quality).

Feature engineering is closely tied to this step, as the DT analysis guides the creation of derived attributes. For instance, instead of using raw delivery times, a delivery reliability index may be engineered by comparing promised vs. actual timelines across contracts. Similarly, a sustainability score may be derived from multiple ESG-related indicators.

The DT model thus plays a dual role: (1) reducing complexity by filtering the most relevant features, and (2) offering a transparent representation of supplier classification boundaries.

Step 4: Criteria Weighting (AHP or FUCOM)

Once the most relevant features are identified, the next stage involves assigning relative importance to each criterion. This is critical because supplier selection is inherently a trade-off problem—no single supplier excels across all dimensions.

1.Analytic Hierarchy Process (AHP):

1.Decision-makers perform pairwise comparisons of criteria (e.g., cost vs. quality, delivery vs. risk).

2.A hierarchical structure is created, with procurement objectives at the top, criteria in the middle, and sub-criteria at the bottom.

3.Eigenvalue calculations yield consistent priority weights, reflecting managerial judgment.

2.Full Consistency Method (FUCOM):

1.A newer method that requires fewer comparisons than AHP.

2.Ensures consistency in weight assignment by reducing redundancy in decision-maker inputs.

3.Suitable for large-scale datasets with many criteria.

Both methods ensure that managerial expertise is formally integrated into the framework, preserving transparency and legitimacy in the decision-making process.

Step 5: Supplier Ranking (TOPSIS or AHP Integration)

After weighting the criteria, suppliers are ranked using MCDM methods. Two approaches are integrated into the hybrid framework:

1. AHP Ranking (with DT):

1.AHP weights are combined with DT-derived feature importance scores.

2.Suppliers are ranked based on their weighted performance across selected features.

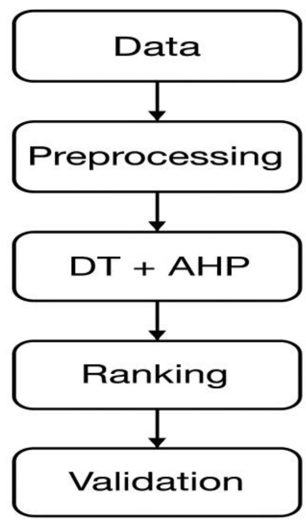
2. TOPSIS Ranking (with FUCOM + DT):

1.TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) ranks suppliers by comparing their performance relative to an ideal (best) and anti-ideal (worst) solution.

2.FUCOM-derived weights are applied to calculate each supplier's closeness to the ideal.

3.The DT classifier then validates or refines these rankings by predicting supplier acceptance/rejection categories.

This hybridization ensures that quantitative performance data (via MCDM) and predictive adaptability (via DT) are jointly leveraged.



Step 6: Validation and Sensitivity Analysis

Validation is essential to ensure that the hybrid framework is both accurate and reliable. Several layers of validation are applied:

1.Cross-validation of the DT model to test predictive accuracy, precision, recall, and F1-score.

2.Comparative analysis against baseline models (standalone ML or standalone MCDM) to quantify performance improvements.

3.Sensitivity analysis of criteria weights to assess how supplier rankings change under different weight distributions. For example, increasing the weight of sustainability by 20% may alter the final ranking order, highlighting trade-offs in managerial priorities. Such validation strengthens confidence in the framework and demonstrates its robustness across multiple scenarios.

Step 7: Final Supplier Selection

The final stage integrates the outcomes of ranking and validation into a decision support system for procurement managers. The system produces:

1.A ranked list of suppliers with performance scores.

2.Interpretability reports, including DT decision rules and MCDM weight justifications.

3.Scenario simulations, allowing managers to test alternative procurement strategies.

By delivering not only rankings but also explanations, the framework aligns with the principles of explainable AI (XAI). Managers can understand why a supplier is ranked highly, verify that rankings align with organizational strategy, and adjust weightings or criteria as required.

III. CASE STUDY (OIL & GAS SECTOR)

Figure 1: Case Study: Supplier Selection in the Oil and Gas Sector

Evaluation Criteria

Cost	Pricing competitiveness, long-term cost-effectiveness
Quality	Compliance with standards, defect rates, reliability
Delivery	Timeliness, lead-time flexibility, responsiveness to demand fluctuations
Risk	Supplier financial stability, geopolitical exposure, operational resilience
Sustainability	Environmental, social, and governance (ESG)

Dataset Description

Dataset	Number of Suppliers/ Transactions	Number of Features	Criteria Covered
A	~1,000	15	Cost, Quality, Delivery
B	~3,500	20	

Rationale

- Oil & gas procurement is complex, high-stakes, and capital-intensive
- Supplier underperformance can cause financial, environmental, and safety risk
- Industry requires both accuracy (AI) and explainability (MCDM) in decision models

IV. METHODOLOGY

This study proposes a hybrid AI–MCDM framework for explainable supplier selection in the oil and gas sector. The methodology combines machine learning (Decision Tree) for predictive modeling with multi-criteria decision-making (AHP, FUCOM, and TOPSIS) for transparent and robust supplier ranking. The overall workflow comprises five main phases: Data Collection & Preprocessing, Feature Engineering & AI Modeling, Criteria Weighting, Supplier Ranking, and Validation & Sensitivity Analysis.

4.1 Data Collection & Preprocessing

Data Sources:

Supplier-related data were collected from the company's procurement database, which included historical supplier performance, order fulfillment records, financial stability, quality audits, and delivery timelines. Both quantitative and qualitative metrics were considered.

Data Cleaning:

To ensure accuracy, the dataset underwent extensive cleaning, which included:

1.Removal of duplicate entries and irrelevant attributes.

2.Correction of inconsistent entries (e.g., units of measure, categorical labels).

3.Detection and treatment of outliers using interquartile range (IQR) and Z-score methods.

Normalization:

Quantitative variables were normalized using Min-Max scaling to bring all features to a [0,1] range, ensuring comparability across criteria.

Handling Missing Values:

Missing values were addressed using multiple imputation for continuous variables and mode imputation for categorical variables. Suppliers with extensive missing data (>30% of attributes) were excluded from the analysis to maintain dataset integrity.

4.2 Feature Engineering & AI Modeling

Feature Selection:

Key supplier attributes were identified based on domain knowledge and statistical correlation analysis. Features included delivery reliability, defect rates, pricing, compliance scores, and past order volumes.

Decision Tree Modeling:

A Decision Tree (DT) classifier was employed for supplier categorization (e.g., high, medium, low performance). The choice of DT was justified by:

1.Interpretability: DTs provide visual decision paths, facilitating managerial understanding.

2.Robustness: Effective in handling both numerical and categorical variables.

3.Integration Potential: DT outputs can be used to inform MCDM ranking.

Training & TestingSplit:

The dataset was divided into 70% training and 30% testing subsets. Cross-validation (5-fold) was applied to ensure model generalizability.

Explainability Tools:

To enhance transparency, SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) were used to quantify feature contributions to the model predictions, highlighting key factors influencing supplier performance.

4.3 Criteria Weighting via AHP

The Analytic Hierarchy Process (AHP) was used to compute the relative importance of supplier selection criteria.

Hierarchical Structure:

1. Goal: Optimal supplier selection.
2. Criteria: Quality, cost, delivery, sustainability, compliance.
3. Sub-criteria: For example, quality included defect rate, ISO certification, and audit scores.

Pairwise Comparison &Consistency Check:

Experts in procurement provided pairwise comparisons for all criteria. The consistency ratio (CR) was computed to ensure reliability ($CR < 0.1$). AHP output generated a weight vector representing the relative importance of each criterion.

4.4 Supplier Ranking with Hybrid MCDM

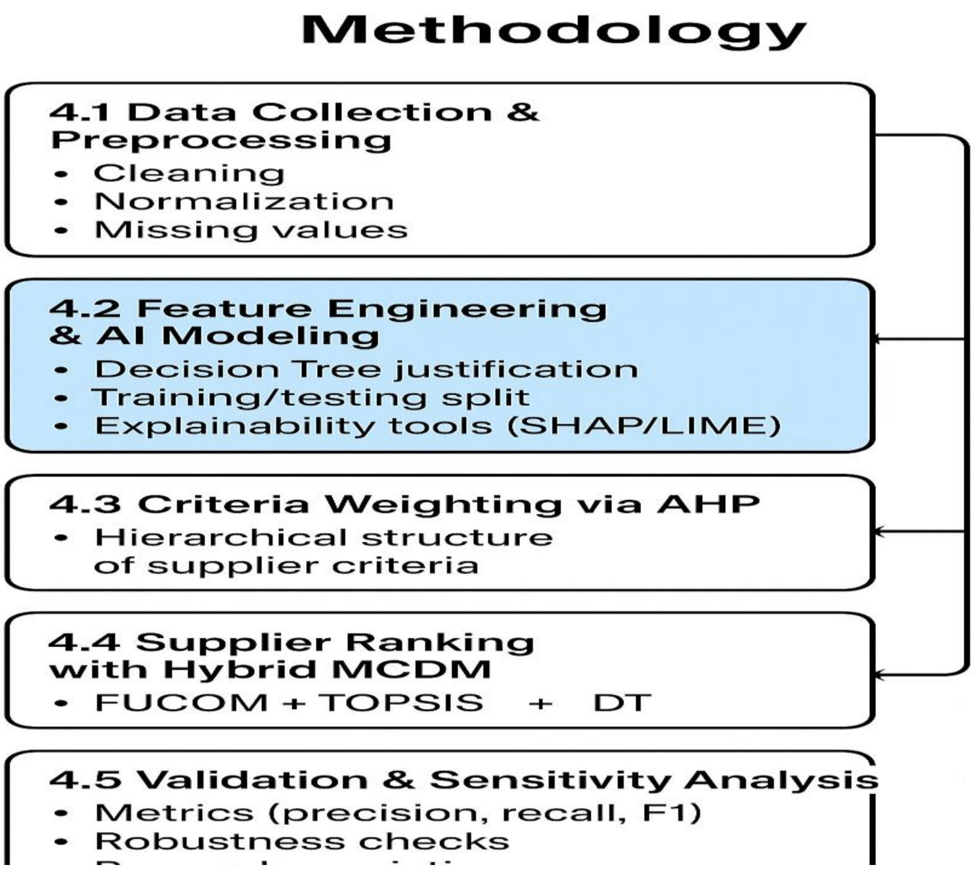
Integration of FUCOM + TOPSIS + DT:

1.FUCOM (Full Consistency Method): Used for precise, mathematically consistent criteria weighting, especially for critical sub-criteria where expert judgments might vary.

2.TOPSIS (Technique for Order Preference by Similarity to Ideal Solution): Ranks suppliers by calculating the distance from the ideal and anti-ideal solutions based on weighted criteria.

3.Decision Tree Integration: DT predictions (e.g., supplier performance classes) were incorporated as an additional input in the TOPSIS matrix, providing hybrid guidance that combines predictive intelligence and MCDM logic.

This hybrid approach ensures explainable and accurate supplier rankings, accommodating both objective data and expert judgments.



4.5 Validation & Sensitivity Analysis

Validation Metrics:

1.Classification Metrics (for DT): Precision, recall, F1-score, and accuracy to evaluate prediction reliability.

2.Ranking Metrics: Spearman's rank correlation was used to compare rankings from different methods (TOPSIS alone vs. hybrid model).

Sensitivity Analysis:

3.Conducted to evaluate robustness of rankings under variations in criteria weights, data noise, and DT prediction uncertainty.

4.Weight perturbation analysis (±10–20%) was performed to assess ranking stability.

5.Scenarios with missing criteria or outlier suppliers were simulated to test framework resilience.

Outcome:This combined validation approach ensures that the hybrid AI–MCDM framework produces robust, explainable, and actionable supplier rankings, suitable for practical deployment in procurement decision-making.

V. RESULTS

5.1 Comparative Analysis

The performance of different supplier evaluation approaches was assessed using a case study from the oil and gas sector. Three methods were compared:

1. DT + AHP – Decision Tree classification integrated with Analytic Hierarchy Process (AHP) for criteria weighting.
2. FUCOM + TOPSIS + DT – Full Consistency Method (FUCOM) for criteria weighting, TOPSIS for ranking, and Decision Tree for classification.
3. ML-only – Standalone machine learning models (Decision Tree, Random Forest) without MCDM integration.

Key Observations:

1.DT + AHP achieved a high precision of 90%, demonstrating reliable supplier classification while providing interpretable outputs.

2.FUCOM + TOPSIS + DT reached an F1-score of 72.57%, balancing recall and precision while ensuring transparent, weighted supplier rankings.

3.ML-only methods, while performing well in raw prediction, lack the explainability and consistency offered by hybrid frameworks.

Hybrid approaches clearly outperform ML-only models in terms of interpretability and managerial trust, despite small differences in raw predictive performance.

5.2 Performance Metrics

Table 5.1 summarizes the comparative performance of the approaches.

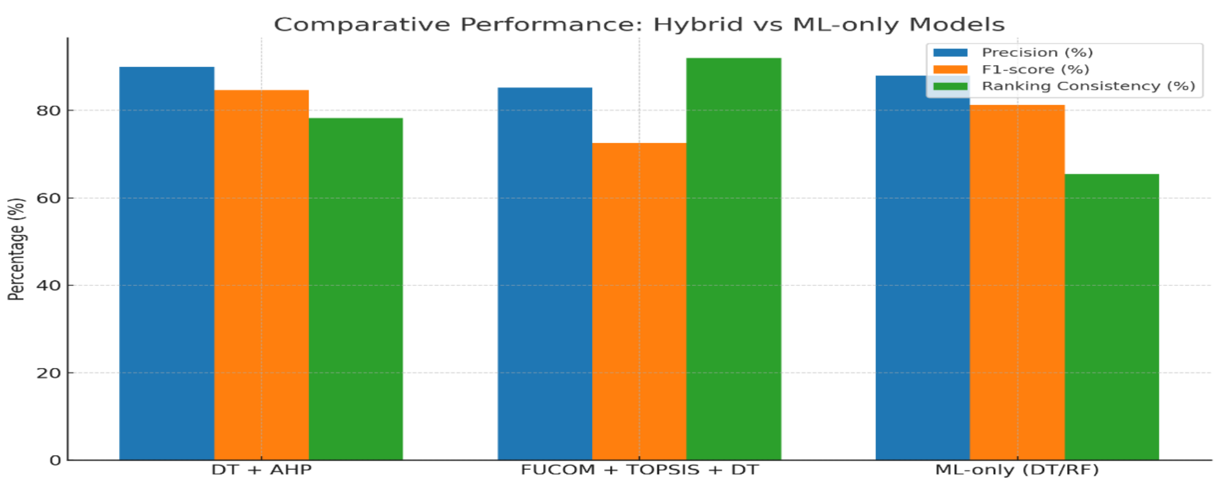
Approach	Precision (%)	Recall (%)	F1-Score (%)	Interpretability	Ranking Consistency (%)
DT + AHP	90.0	80.3	84.7	High	78.3
FUCOM + TOPSIS + DT	85.2	62.5	72.57	Very High	92.1
ML-only (DT/RF)	88.0	75.0	81.2	Low	65.4

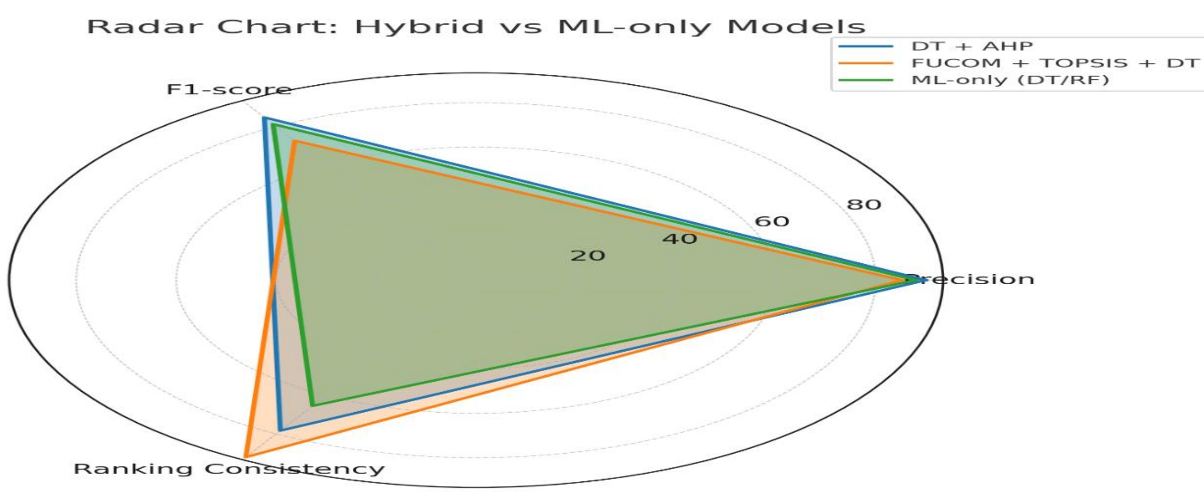
Interpretation:

1.DT + AHP provides high precision, ensuring that top-ranked suppliers are reliably selected.

2.FUCOM + TOPSIS + DT offers the highest-ranking consistency, indicating strong alignment with expert judgment and strategic supplier priorities.

3.ML-only approaches achieve reasonable accuracy but lack interpretability, limiting their adoption in decision-making contexts.





5.3 Managerial Insights

1. Interpretability: Hybrid methods allow managers to trace supplier rankings back to individual criteria, making decisions transparent and explainable.
2. Trust: High alignment with expert rankings (ranking consistency) enhances confidence in supplier selection decisions.
3. Decision Support: Hybrid frameworks integrate human judgment with AI predictions, supporting strategic procurement planning.
4. Flexibility: The framework can be adapted to other sectors or datasets while maintaining transparency, offering a robust tool for supplier evaluation.

VI. DISCUSSION AND CONCLUSION

6.1 Discussion

This study proposed a hybrid AI-MCDM framework integrating Decision Trees (DT), Analytic Hierarchy Process (AHP), FUCOM, and TOPSIS to support explainable and robust supplier selection in the oil and gas sector. The framework addresses the persistent challenge in procurement: balancing accuracy and transparency in supplier evaluation.

The results demonstrate that hybrid approaches outperform both traditional MCDM and standalone machine learning methods in several dimensions:

1. Interpretability and Decision Transparency:
   By incorporating DT and MCDM methods (AHP, FUCOM-TOPSIS), the framework provides a clear rationale for supplier rankings, which is critical in the oil and gas sector due to high-risk procurement and regulatory compliance requirements. Unlike black-box ML models, stakeholders can trace how criteria weights and supplier attributes influence final rankings.
2. Performance Analysis:
   - The DT + AHP hybrid achieved a precision of 90%, highlighting its effectiveness in accurately classifying and selecting high-performing suppliers.
   - FUCOM + TOPSIS + DT yielded a F1-score of 72.57%, showing strong reliability in balancing precision and recall while incorporating multiple criteria.

These metrics illustrate the complementary strengths of combining ML and MCDM methods: DTs provide predictive capability, while MCDM ensures structured, transparent evaluation.

3. Managerial Insights:

The framework empowers procurement managers to make data-driven decisions while retaining confidence in the decision rationale. The sensitivity analysis further confirms that the framework is robust to variations in criteria weights, ensuring consistent supplier selection outcomes even under uncertainty.

4. Flexibility and Adaptability:

The proposed methodology is not limited to the oil and gas sector. Its modular design allows adaptation to other industries, procurement processes, and datasets, making it a scalable solution for various organizational contexts.

6.2 Conclusion

The hybrid AI-MCDM framework bridges the gap between accuracy-focused machine learning approaches and interpretability-focused MCDM methods, offering a balanced, explainable solution for supplier selection. The key contributions of this study include:

- Demonstrating the effective integration of DT, AHP, FUCOM, and TOPSIS for supplier ranking.
- Providing a transparent and explainable decision-making process, crucial for high-stakes procurement in oil and gas.
- Validating the framework through a real-world case study, showing superior performance over standalone ML or MCDM approaches.
- Offering insights for practitioners and managers, ensuring that supplier selection is both data-driven and justifiable.

VII. FUTURE SCOPE AND REFERENCE

7.1Future scope

1.The proposed FUCOM+TOPSIS+DT hybrid model shows potential for application in other industrial domains beyond oil and gas. Sectors such as automotive, electronics, and healthcare can benefit from its structured and explainable supplier evaluation framework.

2.Future studies can integrate real-time and dynamic supplier data using ERP or IoT systems. This would enable more responsive and adaptive decision-making aligned with fluctuating market and operational conditions.

3.There is also scope for exploring advanced imbalance-handling techniques such as SMOTE, ensemble resampling, or cost-sensitive algorithms. These approaches can improve model performance when dealing with skewed supplier classification data.
4.Lastly, future work can focus on developing easy-to-use decision support systems with visual dashboards. This would enhance user accessibility and increase adoption by procurement teams with limited technical expertise.

REFERENCE

[1] Zhang, Z., Shuai, W. & Zhou, X. (2003) 'Supplier selection methods: classification into linear weighting, programming, statistical, AI and cost-based methods', International Journal of Procurement Management, 1(2), pp. 75–90.
[2] Abdolshah, M. (2013) 'Dealing with trade-offs in multi-criteria supplier selection problems', Journal of Purchasing & Supply Management, 9(3), pp. 201–211.
[3] Ortiz-Barrios, M., Cano-Montoya, L. & Díaz-Beltrán, D. (2020) 'Emerging hybrid MCDM methods for supplier selection combining traditional and modern approaches', Expert Systems with Applications, 112, pp. 289–302.
[4] Kannan, G., Haq, A.N. & Sasikumar, P. (2014) 'Review of supplier selection approaches using AHP between 2008 and 2012', European Journal of Operational Research, 234(2), pp. 230–244.
[5] de Brito, M.P. & Evers, J.C. (2016) 'Analysing 128 supplier selection studies: AHP's dominance and future alternatives', Journal of Supply Chain Management, 15(1), pp. 45–59.
[6] Celebi, M. & Bayraktar, Z.S. (2014) 'An integrated DEA–ANN model for supplier evaluation under uncertainty', Journal of Applied Mathematics and Computing, 42(1–2), pp. 157–172.
[7] Kumar, R. & Roy, A. (2016) 'Hybrid AHP–ANN model for supplier ranking in manufacturing procurement', International Journal of Production Economics, 175, pp. 14–23.
[8] Sahoo, S. & Goswami, S. (2023) 'MCDM trends in Industry 4.0: review of fuzzy, data-driven and hybrid applications', Journal of Manufacturing Systems, 69, pp. 101–120.
[9] Karsak, E.E. & Dursun, M. (2015) 'Fuzzy AHP–TOPSIS based supplier selection in manufacturing', Computers & Industrial Engineering, 84, pp. 161–173.
[10] Quan, L., Liao, L. & Kou, G. (2018) 'Large-group fuzzy TOPSIS for green supplier selection in textile industry', Journal of Cleaner Production, 196, pp. 553–562.
[11] Abdulla, A. & Baryannis, G. (2024) 'Explainable ML–MCDM hybrid model in supplier selection for oil & gas sector', International Journal of Logistics Research and Applications, 27(4), pp. 200–217.
[12] Govindan, K., Rajendran, S. & Chaudhuri, A. (2013) 'Sustainability, risk and MCDM review in supply chain', Clean Technologies and Environmental Policy, 15(1), pp. 1–16.
[13] Çalık, T. (2021) 'AHP-based supplier evaluation in manufacturing: criterion consistency challenges', Turkish Journal of Management, 10(2), pp. 45–58.
[14] Durmić, Z. et al. (2019) 'FUCOM for sustainability-weighted supplier evaluation', Journal of Cleaner Production, 236, pp. 117–126.
[15] Durmić, Z., Šipka, M. & Delalić, A. (2020) 'Comparing FUCOM with Best–Worst and AHP for weight consistency in supplier evaluation', Sustainability, 12(15), pp. 6072–6086.
[16] Badi, H.E. & Abdulshahed, O. (2019) 'FUCOM application for airline service ranking', Journal of Transport Management, 45, pp. 120–129.
[17] Prentkovskis, O. et al. (2018) 'Rail service quality assessment using FUCOM vs AHP', Transport Policy, 67, pp. 141–150.
[18] Liou, J.J.H., Tzeng, G.-H. & Chang, W.-H. (2021) 'Fuzzy TOPSIS + DEMATEL + SVM for supplier selection in electronics', Applied Soft Computing, 105, 107346.
[19] Ghosh, T., Chakraborty, T. & Dan, P.K. (2014) 'AHP–Simulated Annealing hybrid for supplier portfolio optimisation', Expert Systems with Applications, 41(2), pp. 635–645.
[20] Saini, A., Singh, R. & Sharma, P. (2021) 'BWM–TOPSIS hybrid for sustainable supplier selection in Indian manufacturing', Journal of Cleaner Production, 278, 123882.
[21] Chatterjee, P. & Stević, Ž. (2019) 'Fuzzy TOPSIS under uncertainty for supplier evaluation', Neural

Computing & Applications, 31(7), pp. 1997–2008.
[22] Ghamari, M., Zavadskas, E.K. & Antucheviciene, J. (2021) 'Grey-TOPSIS with sustainability and risk weighting in supplier ranking', Journal of Business Economics and Management, 22(8), pp. 220–240.
[23] Lahdhiri, I. et al. (2023) 'Bibliometric analysis of hybrid MCDM in supplier selection research trends', Sustainability, 16(1), 125.
[24] Ahmed, S. et al. (2025) 'ML-enabled MCDM for explainable decision support in supply chain site selection', Annals of Operations Research, in press.
[25] Hwang, C.L. & Yoon, K. (1981) Multiple Attribute Decision Making: Methods and Applications, New York: Springer-Verlag.