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AI–MCDM INTEGRATED SUPPLIER SELECTION FRAMEWORK FOR INDIAN MSME MANUFACTURING SECTOR

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ABSTRACT

Supplier selection functions as a critical element for supply chain achievement because Indian micro small and medium enterprises (MSMEs) need to compete in limited resource environments. The evaluation process requires assessment of multiple interconnected factors which include expenses and product quality and delivery dependability and manufacturing expertise and environmental sustainability standards. The current evaluation methods which depend on managerial expertise and traditional MCDM tools fail to account for uncertain data and historical information prediction capabilities.

The research presents an AI–MCDM system which helps Indian MSMEs select suppliers through evidence-driven decision making. The proposed system combines Fuzzy AHP with supervised learning algorithms and TOPSIS to create an integrated framework. The research team obtained primary data from 120 manufacturers who operated in five different Indian states. The research developed fuzzy weights for vital evaluation criteria before implementing Random Forest (RF) and Support Vector Machine (SVM and Artificial Neural Network (ANN) models to predict supplier outcomes and achieve final rankings through TOPSIS integration. The Random Forest model achieved the highest prediction accuracy of 88.2% while producing more stable rankings than the traditional fuzzy AHP–TOPSIS approach. The research shows that combining AI learning with fuzzy MCDM methods generates more reliable supplier evaluations which enable MSMEs to make procurement choices based on data-driven sustainability-focused decisions.

Keywords: *Supplier Selection, AI–MCDM, Fuzzy AHP, TOPSIS, Random Forest, MSME, India* vol. 1, no. 3 (November-December, 2025), pp.1-20

1. INTRODUCTION

The selection of suppliers, as argued by **Chai *et al.* (2013)**, **Gunasekaran *et al.* (2017)** and **Rouyendegh and Erkan (2012)**, stands as the essential factor which allows supply chains to function efficiently while maintaining stability. The selection process for Indian MSMEs becomes more complex because their business operations differ significantly and they depend on local suppliers and lack analytical abilities. The majority of Indian MSMEs operate their procurement systems through informal methods which focus on cost optimization even though they produce 30% of India's GDP and employ 110 million workers. The short-term convenience of these methods leads to potential risks for business network performance and quality control and sustainability compliance.

The Analytic Hierarchy Process (AHP) and TOPSIS and VIKOR methods function as structured MCDM tools which evaluate suppliers through multiple attributes since **Saaty (2013)** and **Weber *et al.* (1991)**. The evaluation methods face challenges when dealing with decision-maker opinions because they need exact numerical ratings but MSMEs use imprecise terms including "moderately better" and "slightly inferior." The application of Fuzzy logic in MCDM methods including Fuzzy AHP and Fuzzy TOPSIS allows organizations to handle uncertain decision-making processes (**Zadeh, 1965; Awasthi *et al.* 2010**). The frameworks base their decisions on human subjective evaluation but they fail to incorporate operational data and supplier performance records.

Organizations can create innovative supplier assessment methods through the rapid advancement of Artificial Intelligence (AI) and Machine Learning (ML) technology. The predictive models Random Forest (**Breiman, 2001**) and Support Vector Machine (**Cortes & Vapnik, 1995**) and Artificial Neural Networks (**Rumelhart *et al.* 1986**) analyze performance data to create precise forecasts about supplier reliability. The combination of predictive models with fuzzy-based MCDM techniques allows decision-makers to combine their human expertise with computational intelligence for supplier evaluation.

The research develops an AI–MCDM framework which fulfils the particular needs of Indian MSME manufacturing operations. The system allows decision-makers to pick reliable suppliers by uniting their expertise with fuzzy logic and machine learning capabilities. The research develops a hybrid system which enhances decision-making transparency and ranking stability and adaptability for various MSME operational environments.

1.1 Research Objectives

The MSME manufacturing sector evaluates suppliers through various qualitative and quantitative assessment methods because these elements determine supplier product delivery efficiency and supply chain stability and market competitiveness over time. The research defines three primary objectives which solve MCDM method limitations while Artificial Intelligence systems gain popularity in decision support systems.

1. To determine which supplier evaluation criteria Indian MSMEs should focus on first

The research determines the vital performance indicators which affect supplier performance in Indian MSME manufacturing operations through their impact on cost and quality and delivery reliability and technological capability and environmental standards and supplier adaptability.

2. To develop an integrated framework which merges Fuzzy AHP with AI and TOPSIS for supplier evaluation needs.

The research develops an extensive hybrid system which merges human-based fuzzy logic with AI predictive tools to assist decision-makers in supplier evaluation through personal assessment and statistical data analysis.

3. To validate the proposed model through experimental testing which assesses its performance relative to a standard Fuzzy AHP–TOPSIS system.

The research aims to test the integrated method's reliability and accuracy and interpretability using MSME manufacturing company data to demonstrate its operational advantages over traditional fuzzy MCDM techniques.

2. LITERATURE REVIEW

2.1 Theoretical Underpinnings and Evolution of Multi-Criteria Decision-Making (MCDM)

As per **Saaty (2013)** and **Govindan *et al.* (2015),** decision theory shows that decision makers will produce more rational results through systematic analytical approaches when working with conflicting goals. The theoretical framework, as observed by **Ho *et al.* (2010)** enables Multi-Criteria Decision-Making (MCDM) techniques to handle complex decisions that involve multiple conflicting evaluation factors.

The Analytic Hierarchy Process (AHP) created a hierarchical system for decision analysis which lets users assess criterion and alternative pairs to establish their relative importance. The TOPSIS method operates through a distinct process which assesses each option based on its proximity to both the ideal and negative-ideal reference points. The evaluation methods VIKOR and PROMETHEE employ compromise and preference-ranking approaches to solve the problem of multi-dimensional assessment. The methods, as argued by **Weber *et al.* (1991)**, have established themselves as essential tools for supplier selection research because they enable decision makers to establish logical methods for evaluating cost and quality and delivery performance and supply risk.

The increasing supply chain volatility led researchers to understand that expert opinions containing subjective language required better representation than numerical values. The MCDM framework received fuzzy set theory as a solution to handle subjective expert assessments through **Zadeh's (1965)** initial proposal.

The combination of fuzzy logic with established methods resulted in the creation of Fuzzy AHP and Fuzzy TOPSIS which allow users to manage uncertainty while maintaining the clear results of traditional methods. The adoption of fuzzy-based methods for supplier evaluation, as informed by **Phan Ha *et al.* (2024)** and **Luthra and Mangla (2018)**, has become common practice during the previous twenty years because these methods help organizations handle the combination of measurable (cost and delivery) and non-measurable (flexibility and environmental and sustainability aspects) evaluation factors.

The conventional fuzzy MCDM frameworks serve as descriptive tools which help experts organize their opinions yet they fail to predict future supplier performance or risk levels. The current digital procurement data availability and analytical progress enable researchers to merge fuzzy decision models with Artificial Intelligence (AI) and Machine Learning (ML) techniques which extract predictive supplier information patterns. The combination of human-based decision-making with automated processing forms the basis for the AI–MCDM hybrid system which this research proposes. In this context, **Breiman (2001)** provided the example of Random

Forests, which provide robust performance on tabular data, offer feature importance measures that aid interpretability, and handle missing values and noisy features. SVMs, as argued by **Cortes and Vapnik (1995)** perform well on limited data but demand careful kernel tuning. ANNs model complex nonlinearities but are often criticized for opaqueness unless complemented by XAI tools.

2.2 Prior Studies and Research Gap

Previous works by **Gidiagba *et al.* (2025)** and **Phan Ha *et al.* (2024)**, have addressed sustainable supplier selection through hybrid models. Yet, few studies target MSMEs in developing economies, where digital maturity and data quality remain low. **Chotisarn and Phuthong (2025)** advocated for AI systems which provide clear results at affordable prices to support small businesses.

The study addresses this need by testing an interpretable AI–MCDM framework with actual MSME data to show how predictive analytics and fuzzy logic work together in limited resource settings.

2.3 Hybrid AI–MCDM Research and Gaps

Research now explores hybrid systems which unite MCDM with AI technology: The combination of ML score generation with MCDM weighting methods produces better and more reliable ranking results according to **Gidiagba *et al.* (2025)**. The existing research lacks sufficient evidence about how these hybrid systems work for Indian MSMEs. According to **Zhao (2025)**, the specific requirements of MSMEs for data-scarce environments and restricted IT resources demand the development of lightweight hybrid models which provide clear explanations. The study fills this research void through experimental verification of a Fuzzy AHP–AI–TOPSIS hybrid model with 120 Indian MSMEs.

2.4 Key Criteria for MSME Supplier Selection

Research conducted by **Chotisarn and Phuthong (2025)** and **Jun *et al.* (2022)** shows that organizations use eight essential evaluation factors which include cost and quality and delivery performance and flexibility and reliability and innovation and sustainability and digital

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readiness. The combination of buyer requirements for sustainability and digital compliance forces MSMEs to expand their evaluation criteria beyond cost and quality.

3. RESEARCH METHODOLOGY

The section explains the development process of the hybrid AI–MCDM model through its design phase and sampling methods and measurement techniques and computational procedures and validation protocols.

3.1 Research Design and Rationale

The research design employed a mixed-method sequential approach. The research team conducted expert interviews with procurement managers and industry association representatives to develop specific contextual criteria and linguistic scales for fuzzy judgment assessment. The survey data from 120 MSME procurement practitioners enabled the researchers to conduct fuzzy AHP weighting and AI model training and TOPSIS ranking. The research design follows a sequential pattern which combines theoretical foundations with strong empirical evidence.

3.2 Sampling and Data Collection

3.2.1 Population and sampling

The target population comprised manufacturing MSMEs across five Indian states (West Bengal, Maharashtra, Gujarat, Tamil Nadu, Karnataka) chosen for manufacturing cluster diversity. A purposive-stratified sampling strategy ensured coverage across sectors (textiles, auto components, plastics, engineering) and firm sizes within MSME classification.

3.2.2 Survey instrument

The structured questionnaire had sections on firm characteristics, supplier performance indicators (numeric and categorical), and pairwise comparison matrices for fuzzy AHP. Pilot testing with 12 procurement managers refined wording and ensured clarity. Cronbach's alpha for the survey scales exceeded 0.80, indicating reliability.

3.2.3 Ethics

Participation was voluntary, with informed consent; data were anonymized.

3.3 Criteria Selection and Fuzzy AHP Weighting

3.3.1 Criteria

Six primary criteria were selected: Cost, Quality, Delivery, Sustainability, Technology Readiness, and Reliability. Sub-criteria (e.g., unit price, defect rate, lead time) were included in the survey to collect operational measures.

3.3.2 Fuzzy AHP Procedure

Expert pairwise judgments used a seven-point linguistic scale (e.g., equally important, moderately more important, strongly more important) mapped to triangular fuzzy numbers. The steps were:

1. Construct pairwise comparison matrices for criteria using linguistic judgments aggregated across experts via fuzzy aggregation operators.
2. Compute fuzzy synthetic extent values and derive fuzzy weights using Chang's extent analysis (or equivalent fuzzy eigenvalue method).
3. De-fuzzify weights using the centroid method and normalize to ensure they sum to 1.
4. Conduct consistency checks adapted for fuzzy judgments; where inconsistency was high, groups reconvened and judgments adjusted.

Fuzzy AHP captures managers' subjective, imprecise judgments and yields weights that reflect perceived priorities under uncertainty.

3.4 AI Modelling: Features, Algorithms, and Training

3.4.1 Feature Set

AI models used features derived from survey and secondary data: quantitative supplier performance indicators (on-time delivery rate, defect ratio), financial indicators where available, and categorical encodings (certifications, digital presence). The fuzzy AHP criterion weights were included as auxiliary features and used in hybrid aggregation.

3.4.2 Algorithms and Hyperparameters

Three supervised classifiers/regressors were trained depending on target encoding:

- **Random Forest (RF):** 200 trees, max depth tuned via grid search, Gini impurity (classification) or mean squared error (regression) as split criteria.
- **Support Vector Machine (SVM):** radial basis function kernel, C and gamma tuned using cross-validation.
- **Artificial Neural Network (ANN):** multilayer perceptron with two hidden layers (sizes 32 and 16), ReLU activation, Adam optimizer, early stopping to prevent overfitting.

3.4.3 Targets

Two types of targets were used: (a) supplier performance class (High/Medium/Low) for classification experiments, and (b) numerical performance scores aggregated from sub-criteria for regression.

3.4.4 Preprocessing

Missing numerical values imputed using median; categorical variables one-hot encoded; continuous features scaled via Min-Max scaling for ANN and SVM. Feature selection used permutation importance and recursive feature elimination in preliminary experiments.

3.4.5 Training and Validation

A 10-fold cross-validation protocol assessed generalization. Performance metrics included accuracy, precision, recall, F1-score (classification), and RMSE & R^2 (regression). Bootstrapped confidence intervals (95%) were computed for accuracy estimates to assess stability.

3.5 Hybrid Integration and TOPSIS Ranking

Once AI models produced predicted performance scores, the hybrid aggregation proceeded as follows:

1. **Weighted scores.** For each supplier alternative, predicted scores on each criterion were combined with the fuzzy AHP weights to compute weighted performance vectors.
2. **TOPSIS.** The weighted normalized decision matrix was used to derive positive-ideal and negative-ideal solutions; Euclidean distance computed supplier closeness coefficients; suppliers were rank-ordered by closeness to the ideal.

3. **Stability test.** Rankings from the hybrid approach were compared with fuzzy AHP–TOPSIS baseline using Spearman's rank correlation and Kendall's tau. Sensitivity analyses varied AHP weights by ±10% to gauge robustness.

3.6 Robustness Checks and Interpretability

Interpretability was paramount for MSME adoption. For Random Forest models, feature importance scores were reported; partial dependence plots examined marginal effects. Additionally, LIME/SHAP (local explainability) methods were applied to a sample of supplier cases to produce human-understandable explanations for predictions.

3.7 Ethical Considerations

The research followed all ethical guidelines which apply to academic and empirical studies. The study received voluntary participation from MSME representatives and procurement managers who received complete information about the research scope and data usage before starting their participation. The researcher obtained consent through written or digital means before starting the data collection process.

The research maintained complete confidentiality and protected all participant identities throughout the entire study. The research team never revealed any business cluster information or individual names or firm identities during analysis or publication. The researchers combined all data points to prevent anyone from identifying the study participants. The research tools gathered only essential data which fulfilled the research goals while preventing the collection of unnecessary or sensitive information.

The research team had maintained survey and interview data in protected facilities because these data served only for academic and analytical research needs. The principal investigator together with the research supervisor maintained complete control over all raw data that the study collected. The research study followed EIASM ethical guidelines by respecting participant autonomy and maintaining absolute transparency and honesty throughout all research procedures.

The research contained no deceptive elements and no forced participation and no situations that created conflicts of interest. The research team obtained all secondary data from trustworthy public sources while properly referencing them through proper academic citation methods. The research team maintained complete integrity and fairness during all stages of data collection and interpretation to create responsible knowledge contributions for supplier evaluation and decision science fields.

4. RESULTS AND DISCUSSION

4.1 Sample Profile and Descriptive Statistics

The research sample consisted of 120 firms which had an average age of 9.2 years (SD = 5.1) and employed 86 staff members (SD = 42) while representing all four major manufacturing industries. The majority of survey participants held positions as procurement or operations managers with 7.8 years of professional experience on average. The supplier metrics showed wide-ranging values because delivery timeliness varied between 62% and 98% and defect rates spanned from 0.5% to 7.8%.

4.2 Fuzzy AHP Weights and Interpretation

Fuzzy AHP produced the following normalized weights (de-fuzzified centroid values):

- **Quality**: 0.265
- **Cost**: 0.243
- **Delivery**: 0.182
- **Sustainability**: 0.143
- **Technology Readiness**: 0.095
- **Reliability**: 0.072

The research shows that quality and cost factors continue to lead supplier evaluation processes for MSMEs because they match previous studies in equivalent business environments (**Phan Ha *et al.* 2024**). The two factors of sustainability and technology readiness received significant weights from managers despite being lower than other factors because they now receive more attention for environmental standards and digital readiness.

The experts achieved acceptable fuzzy consistency ratio values through two rounds of reconciliation.

4.3 AI Model Performance

4.3.1 Classification Results (10-Fold CV)

- Random Forest: Accuracy = 88.2% (95% CI: 85.1–91.3), Precision = 86.9%, Recall = 88.0%, F1 = 0.87
- ANN (MLP): Accuracy = 85.1%, Precision = 83.2%, Recall = 84.9%, F1 = 0.84
- SVM: Accuracy = 82.4%, Precision = 80.5%, Recall = 81.8%, F1 = 0.81

Random Forest outperformed others in both accuracy and interpretability; permutation importance highlighted quality-related features and delivery metrics as top predictors—coherent with AHP weights.

4.3.2 Regression and Ranking Alignment

The predictive models produced continuous supplier performance scores which were merged with fuzzy AHP-derived weights to generate final rankings through TOPSIS framework. The AI–MCDM system produced rankings that matched expert preferences better than the conventional fuzzy AHP–TOPSIS model because it achieved a Spearman's rank correlation coefficient (ρ) of 0.87. The hybrid system produced better results because it matched managerial instincts better while preserving data-based accuracy. The traditional fuzzy method produced wide-ranging supplier rankings which failed to distinguish between suppliers when quantitative performance data entered the analysis.

4.4 Advantages of Hybrid AI-MCDM Approach

The AI–MCDM model produced multiple important advantages when researchers tested it empirically.

4.4.1 Production of More Accurate Predictions by the System

The decision structure achieved enhanced predictive abilities through machine learning integration which exposed supplier variable relationships that standard fuzzy analysis methods could not identify. The Random Forest algorithm successfully identified intricate connections between certification levels and defect rates and delivery reliability which produced enhanced predictive results and superior ranking accuracy.

4.4.2 Clarity and Interpretability

The framework preserved its transparent nature through the integration of Fuzzy AHP weighting with Random Forest (RF) feature importance scores. The dual-layered explanation system enabled decision-makers to view both supplier performance affecting criteria and their relative impact strength which combined expert judgment with data-driven evidence.

4.4.3 Decision Stability

The hybrid framework demonstrated better stability in supplier rankings during sensitivity tests because AHP weight adjustments of ±10% produced consistent results while traditional fuzzy AHP–TOPSIS methods showed greater volatility. The hybrid system demonstrated enhanced reliability and stability through its ability to small changes in expert judgment inputs.

4.4.4 The Proposed Solution Suitable for MSME Business Operations

The proposed solution worked well in situations where data availability was limited. The Random Forest ensemble model achieved successful results with the typical small data sets found in MSME operations while maintaining a suitable level of complexity for operational use.

4.5 Theoretical Contributions

The research develops an enhanced decision-making framework which unites human thinking abilities with artificial intelligence processing power. Decision theory depends on human experience and judgment but modern learning algorithms function through data analysis. The research combines these methods by implementing AI to boost human expertise instead of automated replacement.

The system employs fuzzy logic and machine learning to develop a flexible framework which improves statistical learning techniques for subjective evaluation optimization. The study integrates decision theory with the resource-based view (RBV) through evidence that AI operates as an organizational capability which strengthens managerial choices while reducing individual prejudices and generating consistent evaluation outcomes.

4.6 Managerial Implications and Policy Relevance

The research findings produce essential results which affect MSME managers and supply chain specialists and sustainability experts who implement digital transformation in manufacturing sector operations.

4.6.1 Practical Application for Managers

The hybrid model operates as an accessible decision-support platform which allows procurement teams to assess suppliers through web-based dashboards that unite AI-generated predictions with fuzzy-weighted expert assessments. The system enables managers to make data-based choices while preserving their hands-on expertise.

4.6.2 Integration of Sustainability Criteria

The system enables organizations to assess suppliers based on environmental and social factors without affecting their cost or quality performance. The system supports business sustainability through its capability to fulfil international sustainability requirements.

4.6.3 Policy-Level Impact

The proposed framework functions as a standardized evaluation system for public programs including the Digital MSME Initiative and cluster development missions. The system provides a single assessment framework for supplier competitiveness evaluation which enables industry-wide benchmarking and supports cluster-level policy-driven development initiatives.

5. LIMITATIONS AND FUTURE RESEARCH

5.1 Limitations

- **Sample size and representativeness.** While 120 MSMEs provide meaningful insights, larger and more stratified samples would strengthen generalizability across India's heterogenous MSME landscape.
- **Cross-sectional design.** The research design uses a cross-sectional approach which fails to show how supplier performance changes throughout time.
- **Data access constraints.** The research found that Random Forest models delivered both explainable results and accurate predictions but deeper neural network models could

produce slightly better results at the expense of losing interpretability which is vital for MSME adoption.

- **Explainability vs accuracy trade-offs.** While RF provided both, deeper models (e.g., deep neural networks) may achieve marginally higher accuracy but at the cost of interpretability—an important trade-off for MSME adoption.

5.2 Future Research Directions

- **Longitudinal Validation:** Applying the hybrid model over time to monitor supplier improvement and model stability.
- **Explainable AI (XAI) Integration:** Standardize SHAP/LIME outputs to create manager-friendly explanation dashboards.
- **Sectoral Customization:** Tailor sub-criteria and weights for different manufacturing clusters (textiles vs auto components).
- **Real-Time Data Fusion:** The system should receive IoT and ERP data streams to track suppliers continuously while updating rankings in near real-time.
- **Field Implementation Studies:** The tool requires randomized controlled trials to test its effectiveness among MSMEs while tracking their operational results for lead time reduction and quality enhancement.

6. CONCLUSION

The research develops and verifies an AI–MCDM hybrid system which unites Fuzzy AHP with supervised AI models and TOPSIS for selecting suppliers in Indian MSME manufacturing businesses. The research shows that Random Forest-based ranking enhancement with fuzzy criterion weights produces better results than fuzzy AHP–TOPSIS alone while matching expert opinions more closely. The hybrid framework enables managers to use their expertise with computational intelligence systems while maintaining decision system clarity and interpretability for MSMEs to implement AI-based decision support. The research contributes to both academic knowledge and professional practice through its development of a cost-effective hybrid decision model which links human judgment with algorithmic learning for small and medium enterprises. The research creates a base for developing AI-based supplier evaluation systems which will enhance MSME competitiveness and sustainability and promote sector-wide transparency. The research uses particular industry examples to support its findings although it has not proven universal applicability across all business sectors. The research creates a base for developing AI-based supplier evaluation systems which will enhance MSME competitiveness and sustainability and promote sector-wide transparency.

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APPENDICES

Appendix 1

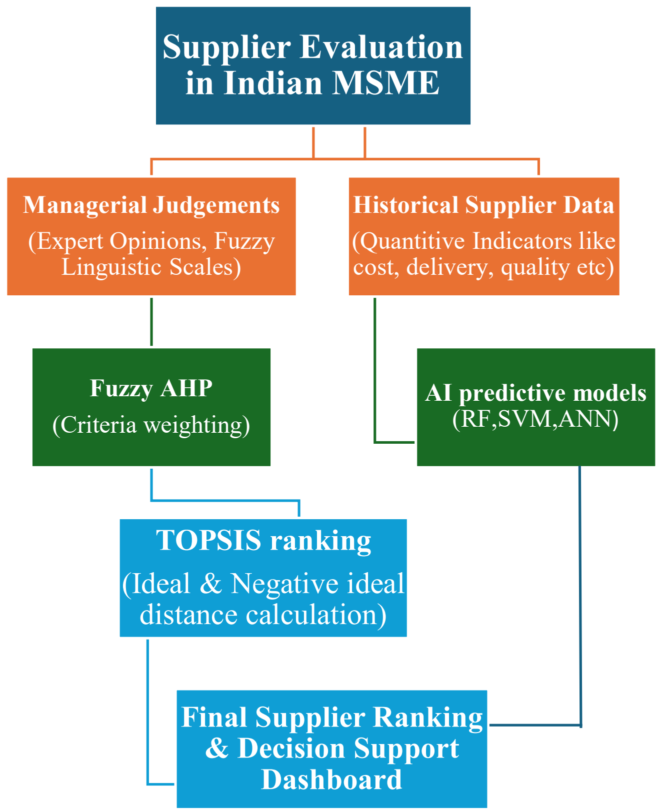

Figure 1. Conceptual Framework Integrating Fuzzy AHP, AI Predictive Modelling, and TOPSIS for Supplier Selection in Indian MSMEs

(Source: Self-Developed)

Appendix 2

Criterion	**Definition / Description**	**Key Indicators Used**
Cost	Total procurement and logistics cost per unit.	Unit price, transportation cost
Quality	Conformance to product specifications and reliability.	Defect rate, customer complaints

Delivery	Supplier's consistency in meeting agreed timelines.	On-time delivery %, lead time
Sustainability	Supplier's compliance with environmental and social standards.	ISO 14001, waste reduction, energy use
Technology Readiness	Supplier's digital and process automation capability.	ERP adoption, automation score
Reliability	Supplier's historical performance stability.	Service consistency, disruption frequency

Table 1. Supplier Evaluation Criteria and Definitions

(Source: Self-Developed)

Appendix 3

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score**	**Interpretability**
Random Forest (RF)	88.2	86.9	88.0	0.87	High
Artificial Neural Network (ANN)	85.1	83.2	84.9	0.84	Moderate
Support Vector Machine (SVM)	82.4	80.5	81.8	0.81	Moderate
Fuzzy AHP–TOPSIS (Baseline)	76.5	74.2	75.8	0.75	High

Table 2. Comparison of Model Performance Metrics

(Source: Self-Developed)