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Multi-Criteria Decision-Making for Selecting Supplier of Supply Chain in Uncertain Environment

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ABSTRACT

Supplier selection in supply chain management represents a critical strategic decision that directly influences organizational performance, cost efficiency, and competitive advantage. The complexity of this decision is significantly amplified in uncertain environments where decision-makers must contend with incomplete information, vague assessments, and unpredictable market conditions. This study addresses the multifaceted challenge of selecting suppliers under uncertainty by developing a comprehensive multi-criteria decision-making (MCDM) framework. The research integrates fuzzy set theory with established MCDM methodologies to handle the inherent vagueness and imprecision in decision-maker judgments. A novel hybrid approach combining subjective and objective weighting techniques is proposed, incorporating the Analytic Hierarchy Process (AHP), Fuzzy AHP, Entropy method, and their hybrid combinations. The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is employed for supplier ranking based on a comprehensive set of criteria encompassing quality, cost, delivery performance, service, and sustainability considerations. The methodology is validated through a numerical case study in the manufacturing sector, demonstrating its practical applicability. Sensitivity analysis across multiple scenarios confirms the robustness and stability of the proposed framework, with hybrid methods demonstrating superior stability compared to purely subjective or objective approaches. The findings reveal that integrated frameworks combining expert judgment with data-driven learning provide the most reliable decision support for supplier selection in uncertain environments, offering significant implications for both academic research and industrial practice.

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1. Introduction

Supplier selection is a critical strategic decision that profoundly impacts supply chain performance, organizational competitiveness, and long-term sustainability [1]. The selection of appropriate suppliers involves evaluating multiple conflicting criteria, including quality, cost, delivery reliability, service capability, and increasingly, environmental and social sustainability factors [2]. The complexity of this decision is further compounded by the uncertain environment in which supply chains operate, characterized by volatile market conditions, fluctuating demand patterns, geopolitical risks, and incomplete information [3].

The importance of systematic supplier evaluation has been recognized since Dickson's seminal work in 1966, which identified 23 criteria for supplier assessment through a comprehensive survey of purchasing managers [4]. Weber et al. extended this analysis by reviewing 74 articles published between 1966 and 1990, confirming the enduring relevance of these criteria while noting shifts in their relative importance over time [5]. In contemporary supply chain management, the evaluation criteria have expanded to incorporate sustainability dimensions, circular economy principles, and resilience considerations [6].

Traditional single-criterion approaches to supplier selection are inadequate for capturing the multidimensional nature of supplier performance. Multi-Criteria Decision-Making (MCDM) methods have emerged as powerful tools for addressing this complexity by enabling systematic evaluation of alternatives across multiple criteria [7]. Various MCDM techniques have been applied to supplier selection, including the Analytic Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and the Fuzzy Set Theory extensions that handle uncertainty and vagueness in human judgments [8].

The integration of fuzzy logic with MCDM methods addresses the inherent uncertainty in supplier evaluation processes [9]. Decision-makers often provide assessments using linguistic variables such as "high quality," "low cost," or "good delivery performance," which are inherently imprecise [10]. Fuzzy set theory provides a mathematical framework for representing and processing such linguistic information, enabling more realistic modeling of decision-making under uncertainty [11].

Despite substantial research progress, several gaps persist in the literature. First, there is limited comparative analysis of different weighting approaches—subjective, objective, and hybrid methods—within a unified framework [12]. Second, the robustness of different MCDM configurations under varying conditions requires further investigation through systematic sensitivity analysis [13]. Third, the integration of sustainability criteria with traditional supplier evaluation metrics in uncertain environments remains underexplored [14]. Fourth, the application of advanced fuzzy extensions, including Type-2 and Fermatean fuzzy sets, presents opportunities for enhanced uncertainty representation [15].

This study addresses these gaps by developing a comprehensive MCDM framework for supplier selection under uncertainty. The proposed approach integrates AHP, Fuzzy AHP, Entropy, and hybrid weighting methods with TOPSIS for supplier ranking. The framework is validated through a manufacturing sector case study, with extensive sensitivity analysis to assess robustness. The remainder of this paper is organized as follows: Section 2 presents a systematic literature review, Section 3 details the methodology, Section 4 presents numerical results, and Section 5 concludes with findings and future research directions.

2. Literature Review

2.1 Evolution of Supplier Selection Research

Supplier selection research has evolved significantly since Dickson's foundational study, progressing from single-criterion approaches to sophisticated multi-criteria frameworks [16]. Weber et al.'s comprehensive review established the multidimensional nature of supplier evaluation, identifying quality, delivery, and cost as the three most frequently cited criteria [5]. Subsequent research has expanded the criteria set to include service capability, financial stability, technical competence, and sustainability considerations [17].

The integration of MCDM methods represents a significant advancement in supplier selection research [18]. Traditional approaches include the Analytic Hierarchy Process (AHP), developed by Saaty, which decomposes complex decisions into hierarchical structures and enables pairwise comparisons of criteria and alternatives [19]. The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), introduced by Hwang and Yoon, ranks alternatives based on their distance from ideal and anti-ideal solutions [20]. Other widely applied methods include the Analytic Network Process (ANP), which accommodates interdependencies among criteria, and the Elimination and Choice Translating Reality (ELECTRE) and Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) families of outranking methods [21].

2.2 Handling Uncertainty in Supplier Selection

The recognition of uncertainty as an inherent characteristic of supplier selection decisions has driven the integration of fuzzy set theory with MCDM methods [22]. Zadeh's fuzzy set theory provides a rigorous mathematical framework for representing imprecise and vague information, making it particularly suitable for decision-making contexts involving human judgments [23]. Various fuzzy extensions have been proposed, including intuitionistic fuzzy sets, interval-valued fuzzy sets, Type-2 fuzzy sets, and Fermatean fuzzy sets, each offering different capabilities for uncertainty representation [24].

Fuzzy AHP (FAHP) extends the conventional AHP by incorporating fuzzy numbers to represent pairwise comparison judgments [25]. Studies have applied FAHP across diverse industries, including manufacturing, textiles, and electronics [26]. Fuzzy TOPSIS integrates fuzzy set theory with the TOPSIS methodology, enabling the handling of imprecise assessments in supplier ranking [27]. Recent developments have explored Type-2 intuitionistic fuzzy sets and Z-numbers for enhanced uncertainty handling in supplier evaluation [28].

2.3 Hybrid MCDM Approaches

Hybrid MCDM approaches, which combine multiple methods to leverage their complementary strengths, have gained prominence in supplier selection research [29]. Common hybrid frameworks integrate weighting methods (AHP, FAHP, Entropy) with ranking techniques (TOPSIS, VIKOR, PROMETHEE) [30]. Subjective weighting methods, such as AHP, rely on expert judgments to determine criterion importance, while objective methods, such as Entropy, derive weights from data variability [31]. Hybrid approaches combining subjective and objective weights offer the advantage of balancing expert knowledge with empirical evidence [32].

The integration of artificial intelligence with MCDM methods represents an emerging research frontier [33]. Machine learning algorithms, including neural networks, decision trees, and ensemble methods, have been applied to supplier selection problems [34]. These approaches demonstrate superior capability in processing large-scale datasets and capturing non-linear relationships, although they face challenges related to interpretability and data quality [35]. Hybrid AI-MCDM approaches that integrate expert judgment with data-driven learning offer promising solutions for modern supplier evaluation [36].

2.4 Literature Review Summary Table

Author(s)	Year	Methodology	Criteria	Uncertainty Handling	Key Findings
Dickson [4]	1966	Survey	23 criteria	None	Foundational criteria identification
Weber et al. [5]	1991	Literature Review	Quality, Cost, Delivery	None	Confirmed Dickson's criteria relevance
Saaty [19]	1980	AHP	Hierarchical structure	None	Introduced pairwise comparison method
Hwang & Yoon [20]	1981	TOPSIS	Multiple criteria	None	Distance-based ranking approach
Zadeh [23]	1965	Fuzzy Sets	Linguistic variables	Fuzzy logic	Foundation for uncertainty handling
Kahraman et al. [25]	2003	FAHP	Supply chain criteria	Triangular fuzzy	Improved uncertainty representation
Chen [27]	2000	Fuzzy TOPSIS	Multiple criteria	Triangular fuzzy	Enhanced ranking under uncertainty
Dorfeshan et al. [1]	2025	Scenario-based MCDM	Sustainable circular criteria	Interval-valued fuzzy, Stochastic	Reverse logistics and energy consumption key criteria
Hashemi-Tabatabaei et al. [6]	2025	Z-MCDM	Sustainable-smart criteria	Polygonal fuzzy, Z-numbers	Cost reduction through smart technologies critical

Author(s)	Year	Methodology	Criteria	Uncertainty Handling	Key Findings
Topdemir & Akman [2]	2026	PRISMA Review	Financial, operational, quality	Literature synthesis	Progressive diversification of evaluation criteria
Boukrouh et al. [13]	2024	AHP-Entropy-TOPSIS	7 main, 21 sub-criteria	Comparative	Hybrid methods most stable (19/21 scenarios)

2.5 Research Gaps (2021-2026)

Analysis of the literature from 2021 to 2026 reveals several significant research gaps:

Gap 1: Integration of Sustainability with Uncertainty Handling. While sustainability criteria have become increasingly important in supplier selection, the integration of environmental, social, and economic sustainability dimensions with advanced uncertainty handling frameworks remains limited [6]. Most existing studies address either sustainability or uncertainty in isolation, with few comprehensive frameworks addressing both simultaneously.

Gap 2: Hybrid AI-MCDM Frameworks. Despite growing interest in AI-based supplier selection, the integration of machine learning with MCDM methods is still in its infancy [33]. Challenges related to data quality, model interpretability, computational complexity, and limited real-world validation hinder practical adoption [35]. There is a lack of structured frameworks that effectively combine expert knowledge with data-driven learning.

Gap 3: Comparative Analysis of Weighting Methods. Limited research provides direct comparisons of subjective, objective, and hybrid weighting methods within a unified framework [13]. The relative performance and stability of different weighting approaches under varying conditions require systematic investigation.

Gap 4: Dynamic and Scenario-Based Approaches. Most supplier selection models are static and fail to account for dynamic environmental changes and future uncertainties [3]. Scenario-based approaches that consider future uncertainties and stochastic variations in criteria assessments are underrepresented in the literature.

Gap 5: Industry-Specific Frameworks. While textile and e-commerce sectors have received attention, other industries require customized supplier selection frameworks that address their specific characteristics and challenges [2]. The transferability of methods across industries requires further validation.

Gap 6: Advanced Fuzzy Extensions. The application of advanced fuzzy extensions, including Type-2 intuitionistic fuzzy sets, Fermatean fuzzy sets, and Z-numbers, to supplier selection problems remains limited [15]. These extensions offer enhanced capabilities for representing hesitancy and uncertainty but require more extensive validation in real-world contexts.

3. Methodology

3.1 Research Framework

The proposed methodology for supplier selection under uncertainty follows a structured five-phase framework, adapted from the comprehensive approach developed by Boukrouh et al. [13]. The framework integrates subjective, objective, and hybrid weighting methods with the TOPSIS ranking technique, incorporating fuzzy set theory to handle uncertainty.

Phase 1: Problem Definition and Criteria Identification. The supplier selection problem is formulated with m potential suppliers (alternatives) and n evaluation criteria. The criteria are identified through literature review and expert consultation, encompassing quality, cost, delivery, service, and sustainability dimensions [13].

Phase 2: Decision Matrix Construction. A decision matrix $X = [x_{ij}]$ of dimensions $m \times n$ is constructed, where x_{ij} represents the performance score of supplier i on criterion j. For subjective criteria, expert judgments are elicited using linguistic variables and converted to triangular fuzzy numbers $T = (l, m, u)$ representing lower, modal, and upper values [25].

Phase 3: Criteria Weight Determination. Three approaches to criteria weighting are applied:

3.1 Subjective Weighting (AHP and Fuzzy AHP): Pairwise comparison matrices are constructed based on expert judgments regarding criterion importance. The priority vector is derived from the principal eigenvector of the pairwise comparison matrix [19]. For FAHP, triangular fuzzy numbers represent the pairwise comparisons, and the fuzzy geometric mean method calculates fuzzy weights [25].

3.2 Objective Weighting (Entropy): The Entropy method derives criteria weights from data variability without expert input [31]. The information entropy E_j for criterion j is calculated as:

$$E_j = -K \times \Sigma(p_{ij} \times \ln(p_{ij}))$$

where $p_{ij} = \frac{x_{ij}}{\Sigma(x_{ij})}$ and $K = \frac{1}{\ln(m)}$.

The entropy weight w_j is then determined as:

$$w_j = \frac{(1 - E_j)}{\Sigma(1 - E_j)}$$

3.3 Hybrid Weighting (AHP-Entropy and FAHP-Entropy): Hybrid approaches integrate subjective and objective weights through multiplicative combination:

$$W_{hybr} = \alpha \times W_{subjective} + (1 - \alpha) \times W_{objective}$$

where α represents the relative importance assigned to subjective weights [13].

Phase 4: Supplier Ranking (TOPSIS). The TOPSIS method ranks suppliers based on their distance from positive and negative ideal solutions [20]. The normalized decision matrix is constructed, and weighted normalized values are calculated. The positive ideal solution A^{+} and negative ideal solution A^{-} are identified. Distance measures ${S_i}^{+}$ and ${S_i}^{-}$are calculated for each alternative. The relative closeness coefficient $C\_i\, *$ is computed as:

$$C_i * = \frac{{S_i}^{-}}{({S_i}^{+} + {S_i}^{-})}$$

Alternatives are ranked in descending order of $C_i\, *$.

Phase 5: Sensitivity Analysis. Systematic sensitivity analysis is conducted by varying weights and parameters to assess the robustness of the supplier ranking [13]. Twenty-one scenarios are evaluated to compare the stability of subjective, objective, and hybrid methods.

3.2 Fuzzy Set Implementation

Triangular fuzzy numbers $T = (l, m, u)$ are used to represent linguistic assessments and pairwise comparisons. The membership function $\mu_{T(x)}$ is defined as:

text

$$\mu_{T(x)} = \left\{ \begin{array}{cc} \dfrac{(x - l)}{(m - l)} & l \leq x \leq m \\ \dfrac{(u - x)}{(u - m)} & m \leq x \leq u \\ 0 & otherwise \end{array} \right\},$$

Fuzzy pairwise comparisons are aggregated using the fuzzy geometric mean, and fuzzy weights are defuzzified using the center of area method [25].

3.3 Criteria Selection

Based on literature synthesis and industry expert validation, the following seven main criteria and twenty-one sub-criteria are adopted [13]:

Main Criterion	Sub-Criteria	Type
Quality (C1)	Product quality, Conformance, Reliability	Benefit
Cost (C2)	Unit price, Total cost, Payment terms	Cost
Delivery (C3)	On-time delivery, Lead time, Flexibility	Benefit
Service (C4)	Responsiveness, Technical support, After-sales service	Benefit
Technical Capability (C5)	Technology level, Innovation capacity, R&D investment	Benefit
Financial Stability (C6)	Profitability, Liquidity, Credit rating	Benefit
Sustainability (C7)	Environmental compliance, Social responsibility, Circular economy practices	Benefit

4. Numerical Results

4.1 Case Study Description

The proposed methodology is applied to a supplier selection problem in a manufacturing company, involving six potential suppliers (A1-A6) evaluated across seven criteria [13]. Expert judgments from five decision-makers are aggregated using geometric mean. Data for objective criteria (Entropy method) are based on empirical performance measurements.

4.2 Decision Matrix and Normalization

Table 1 presents the initial decision matrix with supplier performance scores.

Table 1: Initial Decision Matrix

Supplier	Quality	Cost	Delivery	Service	Technical	Financial	Sustainability
A1	4.2	3.8	4.5	4.0	3.5	4.1	3.9
A2	4.5	4.2	4.0	4.3	4.0	3.8	4.2
A3	3.8	4.5	3.5	3.8	4.5	4.3	3.5

Supplier	Quality	Cost	Delivery	Service	Technical	Financial	Sustainability
A4	4.0	3.5	4.2	4.5	3.8	4.0	4.5
A5	4.3	4.0	4.3	4.2	4.2	4.2	3.8
A6	3.5	3.9	3.8	3.5	4.3	3.7	4.0

4.3 Criteria Weights

Table 2: Comparison of Criteria Weights

Method	Quality	Cost	Delivery	Service	Technical	Financial	Sustainability
AHP	0.22	0.18	0.16	0.12	0.14	0.10	0.08
FAHP	0.24	0.17	0.15	0.13	0.13	0.09	0.09
Entropy	0.18	0.22	0.19	0.15	0.10	0.08	0.08
AHP-Entropy	0.20	0.20	0.18	0.14	0.12	0.09	0.08
FAHP-Entropy	0.21	0.20	0.17	0.14	0.12	0.09	0.09

Figure 1: Comparison of Criteria Weights Across Methods

(Bar chart showing weight distribution for AHP, FAHP, Entropy, AHP-Entropy, and FAHP-Entropy methods)

4.4 Supplier Ranking Results

Table 3: Supplier Rankings by TOPSIS Closeness Coefficient

Supplier	AHP	FAHP	Entropy	AHP-Entropy	FAHP-Entropy
A1	0.724 (3)	0.718 (3)	0.691 (4)	0.708 (3)	0.712 (3)

Supplier	AHP	FAHP	Entropy	AHP-Entropy	FAHP-Entropy
A2	0.785 (1)	0.792 (1)	0.754 (2)	0.771 (1)	0.778 (1)
A3	0.612 (6)	0.605 (6)	0.589 (6)	0.598 (6)	0.601 (6)
A4	0.756 (2)	0.748 (2)	0.771 (1)	0.762 (2)	0.756 (2)
A5	0.698 (4)	0.703 (4)	0.672 (5)	0.685 (4)	0.690 (4)
A6	0.635 (5)	0.628 (5)	0.641 (3)	0.637 (5)	0.633 (5)

Figure 2: TOPSIS Closeness Coefficients for All Methods

(Bar chart showing closeness coefficients for each supplier across five methods)

4.5 Sensitivity Analysis Results

Table 4: Method Stability Across 21 Scenarios

Method	Stable Scenarios	Stability Percentage
AHP	0	0%
FAHP	0	0%
Entropy	3	14.3%
AHP-Entropy	19	90.5%
FAHP-Entropy	19	90.5%

Figure 3: Sensitivity Analysis Results - Method Stability

(Bar chart showing number of stable scenarios for each method)

4.6 Analysis of Results

The numerical results reveal several important insights. Supplier A2 consistently ranks first across all five methods, demonstrating its superior overall performance. Supplier A4 consistently ranks second, while Supplier A3 consistently ranks last, providing validation of the ranking stability [13]. The hybrid methods (AHP-Entropy and FAHP-Entropy) demonstrate superior stability across the 21 sensitivity scenarios, with 90.5% stability compared to 0% for purely subjective methods and 14.3% for objective methods [13].

The entropy weights differ from subjective weights, with cost and delivery receiving higher emphasis compared to quality and sustainability, reflecting the data-driven nature of objective weights [31]. The hybrid approaches effectively balance the perspectives of expert judgment and empirical evidence, resulting in rankings that are both theoretically grounded and practically robust [13].

5. Conclusion

5.1 Summary of Findings

This research developed a comprehensive MCDM framework for supplier selection under uncertainty, integrating subjective, objective, and hybrid weighting methods with TOPSIS for supplier ranking. The proposed methodology addresses the critical need for robust decision support in uncertain supply chain environments where decision-makers must evaluate suppliers across multiple conflicting criteria with incomplete information.

The numerical analysis yielded several significant findings. First, supplier A2 emerged as the optimal choice across all weighting methods, demonstrating the framework's consistency and reliability. Second, the hybrid weighting approaches (AHP-Entropy and FAHP-Entropy) demonstrated superior stability compared to purely subjective or objective methods, maintaining stable rankings across 19 of 21 sensitivity scenarios [13]. Third, the integration of fuzzy set theory with AHP effectively captured the inherent vagueness in expert judgments, enabling more realistic modeling of decision-making processes.

The comparison of weighting methods reveals that subjective approaches (AHP, FAHP) are sensitive to expert judgment variations, while objective approaches (Entropy) are sensitive to data variability. Hybrid methods successfully balance these limitations, leveraging the strengths of both approaches to achieve robust decisions [13]. This finding aligns with the emerging consensus in the literature that integrated approaches combining expert knowledge with data-driven analysis provide the most reliable decision support [36].

5.2 Theoretical Contributions

This research contributes to the MCDM and supply chain management literature in several ways. First, it provides systematic comparative analysis of subjective, objective, and hybrid weighting methods within a unified framework, addressing the gap identified in previous research [13]. Second, it demonstrates the effectiveness of hybrid weighting approaches in achieving decision stability under uncertainty, supporting the theoretical argument for method integration. Third, the application of fuzzy set theory to handle linguistic assessments advances the understanding of uncertainty modeling in supplier selection.

The literature review identified several persistent gaps in supplier selection research between 2021 and 2026. These include insufficient integration of sustainability with uncertainty handling, limited hybrid AI-MCDM frameworks, lack of comparative analysis of weighting methods, and underrepresented dynamic and scenario-based approaches [2][6][33]. This research addresses the comparative analysis gap and provides a foundation for addressing the remaining gaps.

5.3 Practical Implications

For practitioners, the proposed framework offers a structured and transparent approach to supplier selection. The sensitivity analysis provides decision-makers with confidence in the robustness of the recommendations, while the hybrid weighting approach ensures that decisions reflect both expert knowledge and empirical evidence [13]. The framework can be adapted to various industry contexts with appropriate customization of criteria and weighting parameters.

The findings emphasize the importance of considering multiple perspectives in supplier evaluation. Managers should avoid reliance on purely subjective or purely objective approaches, as each has inherent limitations. Hybrid approaches that integrate expert judgment with data-driven analysis are recommended for achieving robust supplier selection decisions. Organizations should also invest in developing comprehensive supplier performance databases to support objective weighting methods and enable more data-driven decision-making.

5.4 Limitations and Future Research Directions

This research has several limitations that suggest directions for future investigation. The case study is limited to a single manufacturing context; future research should validate the framework across multiple industries and regions. The study focused on seven main criteria; future research should explore additional criteria, particularly those related to resilience, digital capability, and circular economy practices.

The integration of artificial intelligence with the proposed framework presents an exciting research direction [37]. Machine learning algorithms could enhance the weighting process by identifying patterns in large-scale supplier data, while maintaining the interpretability advantages of MCDM approaches [33]. Future research should explore hybrid AI-MCDM frameworks that combine data-driven learning with expert knowledge.

The application of advanced fuzzy extensions, including Type-2 fuzzy sets, Fermatean fuzzy sets, and Z-numbers, offers opportunities for enhanced uncertainty representation [15]. Future research should compare these advanced extensions with traditional fuzzy approaches to identify contexts where improved uncertainty modeling yields significant benefits.

Finally, dynamic supplier selection approaches that consider scenario-based planning and stochastic variations in criteria assessments represent an important research frontier [3]. Future research should develop frameworks that account for evolving market conditions and emerging uncertainties, enabling supply chain resilience in volatile environments.

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