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Evaluating Blockchain Integration in Intelligent Logistics Ecosystems: A Comparative MCDM Approach

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ABSTRACT

Objective: Supply chain management in dynamic environments requires advanced digital technologies to enhance transparency, security, and operational efficiency. Blockchain technology has emerged as a promising solution for improving traceability and trust in intelligent logistics ecosystems. The objective of this study is to evaluate and compare blockchain platform alternatives using a structured multi-criteria decision-making framework in order to support technology selection in modern logistics systems.

Methods: This research applies a comparative multi-criteria decision-making approach integrating Analytic Hierarchy Process (AHP), Fuzzy Analytic Hierarchy Process (FAHP), AHP-TOPSIS, and Fuzzy AHP-Fuzzy TOPSIS methods. A hierarchical evaluation model was developed. Expert judgments and literature-based criteria were used to determine weights and assess the relative performance of blockchain platform alternatives.

Results: The evaluation results demonstrate consistent rankings across both crisp and fuzzy decision models. Sensitivity analysis further confirms the robustness of the ranking results under different weighting scenarios.

Conclusion: The findings highlight the importance of scalability, interoperability, and transparency when selecting blockchain platforms for intelligent logistics ecosystems. The proposed framework provides decision-makers with a systematic evaluation tool that can support strategic technology adoption and improve decision quality in supply chain digital transformation initiatives.

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1. Introduction

In today's fast-changing business environment, optimizing supply chains is vital for competitiveness and meeting customer needs. Intelligent logistics, shaped by digital transformation and interconnectivity, demand transparent, secure, and traceable data. These needs are effectively addressed by Blockchain through decentralized, immutable records that build trust, reduce inefficiencies, and streamline operations (Kandarkar & Ravi, 2024).To leverage these capabilities and improve performance, organizations must adopt advanced decision-making methods to evaluate Blockchain platforms.

Multi-criteria decision-making (MCDM) methods have emerged as valuable tools for addressing the multifaceted nature of decision-making in supply chain management (Görçün et al., 2023). These methods allow decision-makers to consider multiple criteria simultaneously, enabling them to make informed decisions that account for various objectives and constraints (Oudani, 2023). Among the plethora of MCDM techniques, Analytic Hierarchy Process (AHP), Fuzzy AHP (FAHP), AHP-TOPSIS, and Fuzzy AHP-Fuzzy TOPSIS (FAHP-FTOPSIS) stand out as prominent approaches known for their efficacy in handling complex decision scenarios (Dožić, 2019).

This article focuses on the exploration, comparison, and integration of these advanced MCDM methods to optimize the selection and prioritization of Blockchain platforms within smart supply chains. By synthesizing the strengths of each method and identifying opportunities for integration, we aim to develop a robust decision-making framework capable of addressing the unique challenges posed by intelligent logistic ecosystems. Specifically, our objective is to enhance traceability, security, and efficiency within supply chains by selecting the most appropriate Blockchain platform to support these goals. This research is positioned as a comprehensive comparative study of multiple multi-criteria decision-making (MCDM) approaches applied within a unified evaluation framework for blockchain adoption in intelligent logistics. By comparing the consistency, robustness, and decision outcomes across both crisp and fuzzy methods, the study provides an integrated understanding of how these techniques perform under varying uncertainty levels

This study's originality lies not in proposing a new MCDM algorithm but in the systematic comparison and integration of four established methods within a unified decision architecture for Blockchain-enabled logistics. It contributes by developing a cross-perspective evaluation hierarchy that aligns business, technical, and operational dimensions; implementing a dual-level analysis that contrasts crisp and fuzzy techniques to assess decision stability; and conducting an extended sensitivity analysis that empirically demonstrates ranking robustness across varying managerial priorities. Together, these elements form a replicable decision-support blueprint for future digital-supply-chain evaluations.

The structure of this paper is as follows: Section 2 provides a detailed background overview of various MCDM methods, highlighting their strengths and limitations. In Section 3, the research methodology used to compare and integrate these methods is explained. Section 4 discusses the limitations of the study and outlines directions for future research. Finally, Section 5 concludes the paper, summarizing the key findings and contributions.

2. Background

2.1 The Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP), developed by Thomas L. Saaty in the 1970s, is a structured decision-making methodology widely used across various fields including operations research, engineering, and management (Saaty, 1977). AHP enables decision-makers to systematically evaluate and prioritize alternatives in complex decision scenarios characterized by multiple criteria and conflicting objectives (Kumar et al., 2017). The process begins by decomposing the decision problem into a hierarchical structure consisting of goals, criteria, sub-criteria, and alternatives (Khan & Ali, 2020). Decision-makers then use pairwise comparisons to assess the relative importance of criteria and alternatives, assigning numerical values based on their perceived significance (Khan & Ali, 2020). These pairwise comparisons are synthesized using Saaty's eigenvector method to derive priority weights, which quantify the relative importance of each criterion and alternative in achieving the overall objectives. AHP's unique feature lies in its ability to handle both qualitative and quantitative data, allowing decision-makers to incorporate subjective judgments and expert opinions into the decision-making process. By providing a systematic framework for structuring and analyzing complex decision problems, AHP facilitates more transparent, consistent, and informed decision-making, thereby helping organizations achieve their goals more effectively and efficiently (Khan & Ali, 2020).

2.2 The Fuzzy Analytic Hierarchy Process (FAHP)

The Fuzzy Analytic Hierarchy Process (FAHP) is an extension of the traditional Analytic Hierarchy Process (AHP), designed to handle uncertainty and imprecision in decision-making scenarios. Introduced as a response to the limitations of AHP in dealing with vague or subjective criteria, FAHP incorporates fuzzy logic principles to capture and represent qualitative judgments more accurately. Unlike AHP, which requires decision-makers to provide crisp pairwise comparisons between criteria and alternatives, FAHP allows for the expression of preferences in linguistic terms or fuzzy sets, enabling decision- makers to convey degrees of membership or uncertainty. By fuzzifying the pairwise comparison matrices, FAHP accommodates the inherent ambiguity and subjectivity in decision data, thereby providing a more flexible and robust framework for decision analysis. The FAHP process involves linguistic variables, fuzzy numbers, and fuzzy logic operations to compute priority weights for criteria and alternatives, facilitating the synthesis of subjective judgments and expert opinions. With its ability to handle vague, imprecise, or qualitative information, FAHP enhances the applicability and effectiveness of the Analytic Hierarchy Process in real-world decision-making contexts, particularly in domains where uncertainty and subjectivity are prevalent.

2.3 AHP-TOPSIS

The AHP-TOPSIS methodology combines two powerful decision-making techniques, the Analytic Hierarchy Process (AHP) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), to address complex decision problems more comprehensively. AHP-TOPSIS integrates the hierarchical structuring and pairwise comparisons of AHP with the preference ranking and similarity analysis of TOPSIS. Initially, AHP is used to establish the relative importance of criteria and alternatives by eliciting pairwise comparisons and deriving priority weights. These weights are then utilized to construct weighted decision matrices for each alternative. Subsequently, TOPSIS is applied to rank the alternatives based on their proximity to the ideal solution and their distance from the negative ideal solution, considering both the positive and negative aspects of each alternative simultaneously. By combining the strengths of AHP in structuring decision problems and TOPSIS in evaluating alternatives, AHP-TOPSIS offers a comprehensive approach to decision-making that accounts for both subjective preferences and objective performance metrics. This methodology enables decision-makers to make more informed and balanced decisions, particularly in scenarios where multiple conflicting criteria need to be considered simultaneously.

2.4 Fuzzy AHP-Fuzzy TOPSIS (FAHP-FTOPSIS)

Fuzzy AHP-Fuzzy TOPSIS (FAHP-FTOPSIS) is an integrated decision- making approach that combines the principles of Fuzzy Analytic Hierarchy Process (FAHP) and Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (FTOPSIS) to address decision problems characterized by uncertainty and imprecision (Saoud et al., 2025). In FAHP-FTOPSIS, fuzzy logic techniques are employed to handle vague or subjective criteria, allowing decision-makers to express preferences in linguistic terms or fuzzy sets (Chatterjee & Stević, 2019). The FAHP phase involves structuring the decision hierarchy, eliciting pairwise comparisons using fuzzy linguistic variables, and deriving fuzzy priority weights for criteria and alternatives. These fuzzy weights capture the uncertainty and ambiguity inherent in decision data, enabling a more nuanced representation of decision-makers' preferences. Subsequently, in the FTOPSIS phase, fuzzy similarity measures are computed to determine the proximity of alternatives to the ideal and negative ideal solutions, considering both the optimistic and pessimistic perspectives. By integrating FAHP and FTOPSIS, FAHP-FTOPSIS provides a comprehensive framework for decision analysis that accommodates both qualitative judgments and quantitative performance metrics (Niazmandi et al., 2024), making it particularly suitable for decision problems in which uncertainty and subjectivity play significant roles.

Table 1. Comparative table of multi-criteria decision-making methods

Method	Main Approach	Strengths	Weaknesses	Applicability
AHP	Hierarchical decomposition of criteria and alternatives with pairwise comparisons	Well-established with clear structure; widely applied across domains (Munier & Hontoria, 2021)	Sensitiveto inconsistency in judgments; accuracy depends on reliable pairwise comparisons (Karthikeyan et al., 2016)	Suitable when preferences are well-defined and data is precise (Ho, 2008)
FAHP	Extension of AHP using fuzzy sets to model uncertainty and subjectivity	Handles imprecision and subjectivity in expert opinions (Liu et al., 2020)	Requires careful definition of fuzzy numbers and can be complex to apply (Zandebasiri & Pourhashemi, 2016)	Usefulin contexts involving vague or linguistic judgments (Jalao et al., 2014)
AHP-TOPSIS	Combines AHP for weighting and TOPSIS for ranking alternatives	Integrates weight precision with distance-based ranking (Sirisawat & Kiatcharoenpol, 2018)	Accuracydepends on AHP weighting quality; more complex for non-experts (Ishak & Wanli, 2020)	Effective for structured decisions where criteria importance and rankings must be separated (Ishak & Wanli, 2020)
FAHP-FTOPSIS	Combines fuzzy AHP with fuzzy TOPSIS for uncertain and subjective contexts	Manages uncertainty in both weighting and ranking; suitable for expert- driven evaluation (Nguyen et al., 2024)	Combining both fuzzy methods increases complexity and requires technical expertise (Nguyen et al., 2024)	Appropriate for multi-criteria decisions under uncertainty and imprecision

Table 1 provides a comparative overview of the several multi-criteria decision-making methods, highlighting their main approaches, strengths, weaknesses, and applicability in various decision-making scenarios.

3. Methodology

This study applies both traditional and fuzzy multi-criteria decision-making methods to develop a comprehensive framework for selecting Blockchain platforms in intelligent logistics. It employs the Analytic Hierarchy Process and TOPSIS, along with their fuzzy counterparts, Fuzzy AHP and Fuzzy TOPSIS. Combining crisp and fuzzy models ensures objective evaluation while addressing subjectivity and uncertainty, resulting in a rigorous and flexible assessment.

Figure 1 illustrates the global workflow of the combined AHP-TOPSIS and FAHP-FTOPSIS methodologies used to assess and rank selected Blockchain platforms deployed in logistics scenarios. Although the analysis draws upon three widely adopted blockchain platforms used in logistics—TradeLens, VeChainThor, and OriginTrail—their names are anonymized in the decision matrices as F1, F2, and F3. This anonymization serves two purposes: first, to preserve objectivity by preventing brand bias in expert evaluations, and second, to ensure comparability by focusing solely on technical and operational performance rather than commercial positioning. Each alternative represents a distinct blockchain category (F1: consortium-based enterprise platform; F2: public-permissioned hybrid system; F3: fully decentralized public network). The performance indicators used for scoring were derived from verified technical documentation, platform whitepapers, and industry case reports available in the public domain. Thus, while the labels are abstract, the underlying data reflect real and operational blockchain infrastructures currently used in logistics contexts.

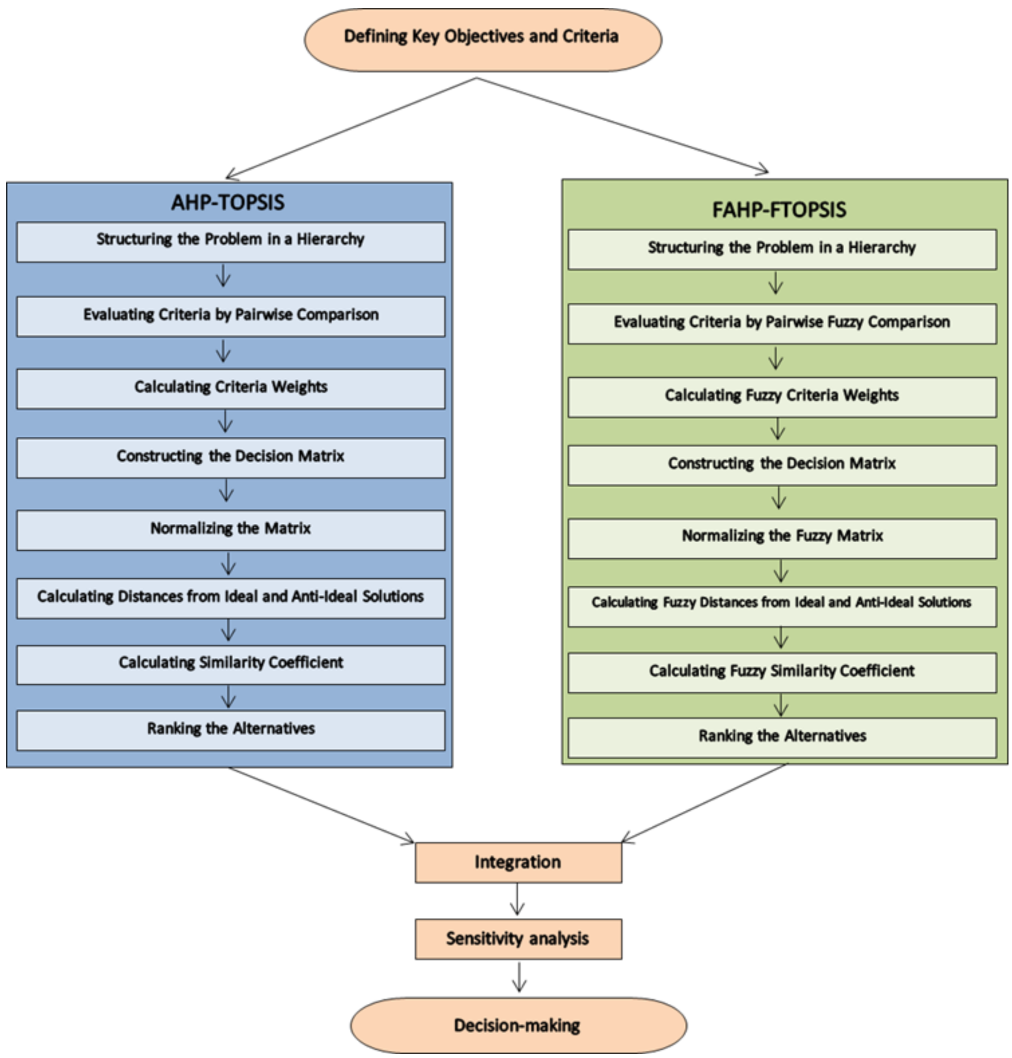

Figure 1. Integrated Workflow of AHP-TOPSIS and FAHP-FTOPSIS

3.1 AHP-TOPSIS framework

This approach consists of the following steps:

1. Identification of Key Objectives and Criteria:

- Defining the primary goals of integrating Blockchain platforms into the supply chain, such as improving traceability, enhancing security, and increasing efficiency.

- Criteria Selection: Identifying the critical criteria for evaluating the Blockchain platforms.

2. Stakeholder Analysis and Requirement Gathering:

- Stakeholder Mapping: Identify all relevant stakeholders, including suppliers, manufacturers, distributors, and customers. Understand their roles and interests in the supply chain.
- Requirement Elicitation: Gather stakeholder requirements to align the framework with their needs, addressing inefficiencies and desired improvements.

3. Multi-Criteria Decision Making (MCDM) Framework:

- Criteria Weighting: Using MCDM techniques such as the Analytic Hierarchy Process (AHP) to assign weights to each criterion based on their importance.
- Alternative Evaluation: Evaluating different Blockchain platform integration scenarios using techniques like TOPSIS to rank the alternatives based on their performance against the weighted criteria.

Table 2. Hierarchy of criteria

Main Criteria	Sub-criteria	Description
Business Environment Perspective	B1: Agility	Ability of the platform to adapt to evolving logistics needs and standards
	B2: Market Adoption	Level of adoption and trust in the logistics industry
	B3: Vendor Support	Availability of technical and business support from the platform provider
Technical Infrastructure	T1: Scalability	Capacity to handle high transaction volumes and large data loads
	T2: Interoperability	Evaluates the ability to interface seamlessly with existing systems and platforms (ERP, IoT, partners), enabling smooth data exchange
	T3: Security	Assesses the cryptographic strength and resilience to attacks
Platform Features	P1: Smart Contract Capabilities	Flexibility and robustness of automated process enforcement
	P2: Data Transparency	Degree of visibility and traceability ensured by the platform
	P3: Compliance and Auditability	Assesses ease of ensuring regulatory compliance and auditing
Operational Perspective	O1: Cost Efficiency	Assesses total cost of ownership (licensing, implementation, operations)
	O2: Implementation Complexity	Assesses difficulty and duration of deploying the platform
	O3: Performance Reliability	Assesses uptime, latency, and transaction speed under logistics load

Table 2 presents a hierarchical set of criteria for evaluating Blockchain platform selection in intelligent logistics. These are grouped into four perspectives:

1. **Business Perspective**: This perspective assesses the platform's ability to meet dynamic business requirements and support strategic decision- making.
   - **Agility**: Evaluates how well the platform adapts to evolving logistics demands, regulatory changes, and market dynamics.
   - **Market Adoption**: Measures the extent of real-world use, maturity, and trust the platform has gained within the logistics sector.
   - **Vendor Support**: Considers the availability and quality of support, documentation, and ecosystem development provided by the platform's maintainers.
2. **Technical Infrastructure:** This perspective focuses on the platform's technical capabilities to ensure seamless and secure integration within logistics operations.
   - **Scalability**: Examines the ability of the platform to handle high transaction volumes and data loads without performance degradation.
   - **Interoperability**: Assesses how effectively the platform integrates with existing systems (e.g., ERP, TMS) and supports cross-platform data exchange.
   - **Security**: Evaluates the robustness of the platform's cryptographic mechanisms and its resilience to cyber threats.
3. **Platform Features**: This perspective considers the functional capabilities embedded within the Blockchain platform that enhance supply chain traceability and automation.
   - **Smart Contract Capabilities**: Assesses the flexibility, reliability, and automation potential of the platform's smart contract functionality.
   - **Data Transparency**: Measures the extent to which the platform ensures traceability and visibility of transactions across stakeholders.
   - **Compliance Auditability**: Evaluates the platform's ability to support regulatory compliance and provide verifiable audit trails.
4. **Operational Impact**: This perspective evaluates the practical implications of platform implementation on supply chain operations.
   - **Cost Efficiency**: Analyzes the total cost of ownership, including implementation, licensing, and operational expenses.
   - **Implementation Complexity**: Considers the ease and duration of deployment, integration, and onboarding.
   - **Performance Reliability**: Measures the platform's consistency in terms of uptime, latency, and overall performance under real-time logistics conditions.

These criteria ensure a thorough and objective evaluation of Blockchain platforms, addressing both strategic alignment and operational feasibility to support the selection of solutions that enhance traceability, security, and efficiency in supply chains.

Table 3. Pairwise Comparison Matrix of the Main Criteria for Blockchain Platform Selection

Criteria	Business Perspective	Technical Infrastructure	Platform Features	Weight
Business Perspective	1.00	2.00	3.00	0.400
Technical Infrastructure	0.50	1.00	2.00	0.260
Platform Features	0.33	0.50	1.00	0.180
Operational Impact	0.50	0.67	1.00	0.160

Table 3 presents the pairwise comparison of main criteria for evaluating Blockchain platform selection in intelligent logistics. Criteria are rated by relative importance on a 1 to 9 scale, producing weights that reflect decision-makers' strategic, technical, functional, and operational priorities.

To ensure the reliability of the pairwise comparison matrix presented in Table 3, the Consistency Ratio (*CR*) was calculated following the standard AHP procedure. The principal eigenvalue of the matrix was approximated as λmax = 4.06. The Consistency Index (*CI*) was computed using equation 1:

$$CI = \frac{\lambda max\ -\ \mathrm{n}}{n\ -\ 1} = \frac{4.06 - 4}{3} = 0.02 \tag{1}$$

Given the Random Index *RI* = 0.90 for a 4 × 4 matrix, the resulting Consistency Ratio (*CR*) is calculated using equation 2:

$$CI = \frac{CI}{RI} = \frac{0.02}{0.90} \approx 0.022 \tag{2}$$

Since *CR* < 0.10, the comparison matrix is considered consistent and acceptable, thus validating the reliability of the weights derived from the AHP process.

Table 4 illustrates the pairwise comparison of the sub-criteria under the Business Perspective. Agility, Market Adoption, and Vendor Support are evaluated based on their relative importance in the decision-making process for selecting Blockchain platforms. The resulting local weights indicate which business-related factors are considered most critical in the platform selection process.

Table 4. Pairwise Comparison Matrix of Sub-Criteria for Business Perspective

Sub-Criteria	Agility	Market Adoption	Vendor Support	Weight
Agility	1.00	2.00	3.00	0.500
Market Adoption	0.50	1.00	2.00	0.300
Vendor Support	0.33	0.50	1.00	0.200

To verify the internal consistency of the pairwise comparison matrix for the Business Perspective sub-criteria (Table 4), the Consistency Ratio (CR) was calculated. Using the same formulation as in equations 1 and 2, the normalized weight vector was used to estimate the principal eigenvalue $\lambda max \approx 3.05$, leading to a Consistency Index (CI) of:

$$CI = \frac{3.05 - 3}{2} = 0.025$$

Given that the Random Index for a 3×3 matrix is $RI = 0.58$, the resulting Consistency Ratio is:

$$CR = \frac{0.025}{0.58} \approx 0.043$$

Since $CR < 0.10$, the matrix satisfies the consistency condition and the derived weights can be considered reliable for subsequent analysis.

Table 5. Normalized Weightings of Sub-Criteria

Main Criteria	Sub-Criteria	Normalized Weight
Business Perspective	Agility	0.500
Business Perspective	Market Adoption	0.300
Business Perspective	Vendor Support	0.200
Technical Infrastructure	Scalability	0.400
Technical Infrastructure	Interoperability	0.300
Technical Infrastructure	Security	0.300
Platform Features	Smart Contract Capabilities	0.350
Platform Features	Data Transparency	0.400
Platform Features	Compliance & Auditability	0.250
Operational Impact	Cost Efficiency	0.400
Operational Impact	Implementation Complexity	0.300
Operational Impact	Performance Reliability	0.300

Table 5 presents the normalized weightings of sub-criteria, indicating the relative importance of each sub-criterion within its corresponding main criterion.

The following table 6 presents the input values for the TOPSIS analysis, in which each alternative is evaluated against the defined criteria. The ideal ($A*$) and negative-ideal ($A-$) solutions represent the best and worst performance observed for each criterion. These benchmarks are used to calculate the relative closeness of each platform to the ideal, thereby enabling a clear and structured ranking of the alternatives.

The input values used in Table 6 were derived through a combined evidence-based and expert-driven process. First, secondary data were collected from both academic and industry sources to establish baseline performance indicators for the evaluated blockchain platforms. Key scholarly references include Jensen et al. (2019), who provide an in-depth analysis of TradeLens, and the bibliometric review by Logistics (2021), which synthesizes blockchain capabilities and adoption drivers in logistics and supply chain contexts. These academic findings were complemented by technical specifications reported in publicly available platform documents such as the VeChainThor and OriginTrail whitepapers. To ensure the reliability of these inputs, values were cross-checked across multiple independent sources and normalized using a consistent linguistic-to-numerical scale adapted from Chatterjee and Stević (2019). Bias was reduced by relying only on publicly verifiable, documented indicators (such as transaction throughput, interoperability features, and consensus mechanisms) rather than subjective opinion. All criteria weights and performance values were also tested for internal logical consistency through the AHP consistency ratio (CR < 0.1), ensuring coherence in the evaluation process.

Table 6. Input Values for TOPSIS Analysis

Criteria	F1	F2	F3	A* (Ideal)	A- (Negative- Ideal)
Agility	0.80	0.70	0.75	0.80	0.70
Market Adoption	0.85	0.60	0.65	0.85	0.60
Vendor Support	0.80	0.70	0.60	0.80	0.60
Scalability	0.75	0.85	0.80	0.85	0.75
Interoperability	0.70	0.65	0.80	0.80	0.65
Security	0.90	0.85	0.80	0.90	0.80
Smart Contract Capabilities	0.70	0.85	0.75	0.85	0.70
Data Transparency	0.80	0.85	0.90	0.90	0.80
Compliance & Auditability	0.85	0.75	0.70	0.85	0.70
Cost Efficiency	0.60	0.75	0.80	0.80	0.60
Implementation Complexity	0.40	0.60	0.70	0.70	0.40
Performance Reliability	0.85	0.80	0.75	0.85	0.75

The performance scores for each alternative (F1–F3) were derived from a synthesis of multiple evidence sources and expert validation. Initial values were extracted from publicly available documentation and whitepapers of three representative blockchain platforms used in logistics: TradeLens (IBM & Maersk, 2023), VeChainThor (VeChain Foundation, 2024), and OriginTrail (Trace Labs, 2024). These raw qualitative assessments (e.g., “high”, “medium”, “low”) were converted into normalized quantitative scores on a [0 – 1] scale following the linguistic-to-numeric mapping used in prior MCDM literature (e.g., Chatterjee & Stević, 2019; Nguyen et al., 2024). Subsequently, six domain experts (three supply-chain managers, two blockchain solution architects, and one academic researcher) independently reviewed and adjusted the scores through a Delphi-style consensus process to ensure consistency across criteria. The final averaged scores presented here represent the consensus estimates of each platform’s relative performance across the twelve evaluation sub-criteria.

Although the actual platform names have been anonymized in this study to promote objective comparison and generalizability, their evaluations were informed by credible technical sources. These include detailed case studies on Blockchain-based supply chain systems whitepapers outlining enterprise integration capabilities, and documentation from Blockchain-as-a-Service (BaaS) platforms actively deployed in production environments.

This anonymization strategy allows the study to focus on evaluating platform capabilities based on performance criteria rather than brand perception, while maintaining reproducibility through clear referencing of the underlying source materials.

The following Table 7 presents the weighted normalized decision matrix used. Criterion weights, obtained via AHP, are applied to the performance scores of the three platforms F1, F2 and F3, thereby reflecting each attribute's relative importance. This matrix is then passed to the TOPSIS procedure, which ranks the alternatives by their closeness to the ideal blockchain solution for supply-chain use.

Table 7. Normalized and Weighted Evaluation Matrix

Criteria	F1	F2	F3
Agility (0.500)	0.400	0.350	0.375
Market Adoption (0.300)	0.255	0.180	0.195
Vendor Support (0.200)	0.160	0.140	0.120
Scalability (0.400)	0.300	0.340	0.320
Interoperability (0.300)	0.210	0.195	0.240
Security (0.300)	0.270	0.255	0.240
Smart Contract Capabilities (0.350)	0.245	0.298	0.263
Data Transparency (0.400)	0.320	0.340	0.360
Compliance & Auditability (0.250)	0.213	0.188	0.175
Cost Efficiency (0.400)	0.240	0.300	0.320
Implementation Complexity (0.300)	0.120	0.180	0.210
Performance Reliability (0.300)	0.255	0.240	0.225

Table 8 presents the final evaluation of the Blockchain platform alternatives (F1, F2, and F3) based on their respective distances from the ideal and negative-ideal solutions, calculated using the TOPSIS method.

Table 8. Final Assessment and Ranking of Alternatives

Alternative	D^* (Ideal)	$D-$ (Negative-Ideal)	Ri (Closeness)	Rank
F1	0.120	0.085	0.415	2
F2	0.110	0.100	0.476	1
F3	0.150	0.065	0.302	3

The distance to the ideal solution (D^*) represents how far each Blockchain platform alternative is from the best possible performance across all evaluation criteria, while the distance to the negative-ideal solution $D-$ indicates the extent to which an alternative avoids the worst-case outcomes. The relative closeness (Ri) is calculated for each alternative to determine its ranking, with higher values reflecting greater proximity to the ideal configuration. Based on the results, alternative F2 emerges as the closest to the ideal solution, followed by

F1, while F3 ranks third. These results provide a clear quantitative basis for selecting the most appropriate Blockchain platform for integration in intelligent logistic environments.

Table 9. Extended Sensitivity Analysis of Blockchain Platform Rankings under Criteria Weight Variation

Instance	Weight Variation	F1	F2	F3	Ranking Order
Instance 1	Base Weights	0.415	0.476	0.302	F2 – F1 – F3
Instance 2	+10% on Business Perspective	0.429	0.462	0.309	F2 – F1 – F3
Instance 3	+10% on Technical Infrastructure	0.421	0.468	0.298	F2 – F1 – F3
Instance 4	+10% on Platform Features	0.410	0.479	0.309	F2 – F3 – F1
Instance 5	+10% on Operational Impact	0.400	0.470	0.324	F2 – F3 – F1
Instance 6	+10% on Agility	0.430	0.450	0.296	F1 – F2 – F3
Instance 7	+10% on Security	0.435	0.446	0.284	F1 – F2 – F3
Instance 8	+10% on Interoperability	0.416	0.475	0.305	F2 – F1 – F3
Instance 9	+10% on Cost Efficiency	0.390	0.460	0.345	F2 – F3 – F1
Instance 10	+10% on Smart Contracts	0.410	0.470	0.322	F2 – F3 – F1
Instance 11	Equal Weights	0.440	0.450	0.330	F2 – F1 – F3

Table 9 presents the results of the sensitivity analysis conducted to evaluate the robustness and adaptability of three Blockchain platform alternatives (F1, F2, and F3) within intelligent logistic ecosystems. In each of eleven scenarios, one decision criterion’s weight is increased by 10% while remaining weights are proportionally reduced, preserving the normalized sum of one and simulating shifted managerial priorities.

The analysis reveals that F2 retains first place in most cases, demonstrating balanced robustness across attributes. F1 overtakes when security or business-governance factors dominate, whereas F3 advances when low cost and operational simplicity are paramount, yet falls behind under integration demands. These patterns confirm the framework’s reliability for decision support.

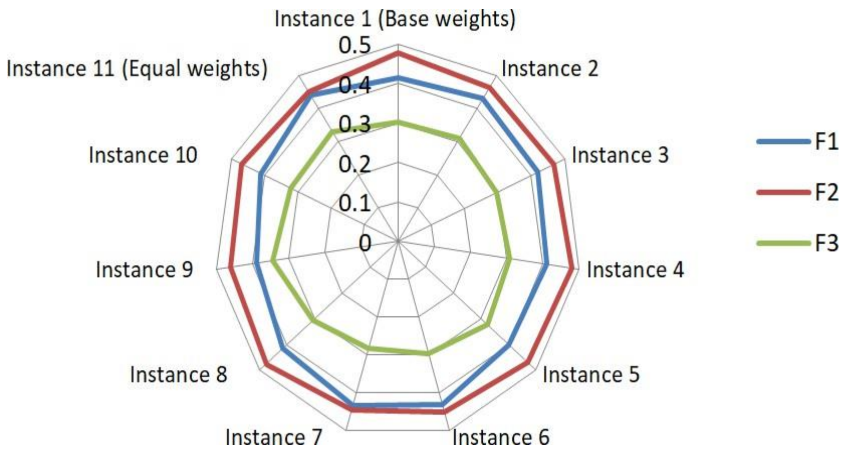

Figure 2. Sensitivity Analysis

Figure 2 displays a radar chart comparing blockchain platform alternatives (F1, F2, and F3) across eleven weighting scenarios. In each experiment, decision criteria weights were varied systematically by ±10% while maintaining total normalization. The values plotted on the radial axes represent the TOPSIS closeness coefficients (Ri), which range from 0 (worst) to 0.5 (best) in this figure. These values were normalized using the classical TOPSIS formula, based on Euclidean distances to the ideal and anti-ideal solutions for each instance.

Alternative F2 encloses the largest area, demonstrating robust performance under most conditions. F1 overtakes when security or governance is emphasized, whereas F3 improves when cost efficiency and operational simplicity receive highest priority.

To complement the sensitivity analysis, two global quantitative measures were employed to assess the robustness of the rankings obtained across the different weighting scenarios.

First, the coefficient of variation (*CV*) of the ranks was calculated for each alternative. This measure evaluates the relative dispersion of an alternative's ranking across the 11 instances. It is defined as in Equation (3):

$$CV = \sigma_i / \bar{r}_i \quad (3)$$

where σ_i is the standard deviation of the ranks and $\bar{r}_i$ is the average rank of the alternative. A lower CV indicates greater ranking stability, suggesting that the alternative consistently performs similarly across scenarios.

Secondly, the Spearman rank correlation coefficient (ρ) was used to measure the similarity between the rankings in each instance and the base case (Instance 1). It is calculated using the formula given in Equation (4):

$$\rho = 1 - (6 \Sigma d_i^2) / (n (n^2 - 1)) \quad (4)$$

where d_i is the difference in rank for alternative i between two instances, and n is the total number of alternatives. A value of ρ close to 1 indicates a high degree of ranking consistency.

The results showed that Alternative F2 exhibited the lowest coefficient of variation, confirming its robust top performance across different weighting schemes. Alternative F1 also showed relatively stable behavior, while F3 demonstrated higher variability but improved in specific cost-focused configurations. Additionally, the average Spearman correlation across all instances was approximately ρ = 0.97, indicating a very high overall stability in the ranking outcomes.

3.2 FAHP-FTOPSIS framework

To address uncertainty and subjectivity, this study extends the analysis by employing the Fuzzy Analytic Hierarchy Process and Fuzzy TOPSIS. These methods enable a more nuanced evaluation by incorporating linguistic judgments and imprecise data through fuzzy logic.

3.2.1 Fuzzy AHP Methodology

The FAHP process begins with the fuzzification of the pairwise comparison matrices for the main criteria and their respective sub-criteria. Triangular fuzzy numbers (TFNs) are used to represent linguistic terms, providing a flexible framework for capturing subjective judgments. Table 10 presents the fuzzified pairwise comparison matrix for the main criteria.

Table 10. Fuzzy Decision Matrix for Blockchain Platform Alternatives (FAHP–FTOPSIS)

Sub-Criteria	F1	F2	F3
Agility	(0.6, 0.7, 0.8)	(0.5, 0.6, 0.7)	(0.5, 0.6, 0.7)
Market Adoption	(0.7, 0.8, 0.9)	(0.5, 0.6, 0.7)	(0.4, 0.5, 0.6)
Vendor Support	(0.7, 0.8, 0.9)	(0.6, 0.7, 0.8)	(0.5, 0.6, 0.7)
Scalability	(0.6, 0.7, 0.8)	(0.7, 0.8, 0.9)	(0.6, 0.7, 0.8)
Interoperability	(0.5, 0.6, 0.7)	(0.6, 0.7, 0.8)	(0.7, 0.8, 0.9)
Security	(0.8, 0.9, 1.0)	(0.7, 0.8, 0.9)	(0.6, 0.7, 0.8)
Smart Contract Capabilities	(0.6, 0.7, 0.8)	(0.7, 0.8, 0.9)	(0.6, 0.7, 0.8)
Data Transparency	(0.7, 0.8, 0.9)	(0.8, 0.9, 1.0)	(0.7, 0.8, 0.9)
Compliance & Auditability	(0.8, 0.9, 1.0)	(0.7, 0.8, 0.9)	(0.6, 0.7, 0.8)
Cost Efficiency	(0.5, 0.6, 0.7)	(0.7, 0.8, 0.9)	(0.8, 0.9, 1.0)
Implementation Complexity	(0.3, 0.4, 0.5)	(0.5, 0.6, 0.7)	(0.6, 0.7, 0.8)
Performance Reliability	(0.7, 0.8, 0.9)	(0.7, 0.8, 0.9)	(0.6, 0.7, 0.8)

The traditional AHP pairwise comparison matrix was converted into Triangular Fuzzy Numbers (TFNs) to account for the imprecision in judgments. Each pairwise comparison value was replaced with a TFN, defined as (L,M,U)(L, M, U)(L,M,U), where LLL represents the lower bound, MMM the most likely value, and UUU the upper bound. The TFNs were assigned based on the linguistic scale of importance, as follows:

Fuzzy pairwise comparisons were aggregated using geometric means, normalized to obtain synthetic extent values, and defuzzified with the centroid method to produce crisp sub-criterion weights. Table 11 summarizes the FAHP results, identifying agility, scalability, and transparency as key factors in selecting Blockchain platforms for intelligent logistics.

Table 11. Fuzzy Weights of Sub-Criteria (FAHP Results)

Sub-Criteria	Fuzzy Weight (l, m, u)
Agility	(0.45, 0.50, 0.55)
Market Adoption	(0.25, 0.30, 0.35)
Vendor Support	(0.15, 0.20, 0.25)
Scalability	(0.35, 0.40, 0.45)
Interoperability	(0.25, 0.30, 0.35)
Security	(0.25, 0.30, 0.35)
Smart Contract Capabilities	(0.30, 0.35, 0.40)
Data Transparency	(0.35, 0.40, 0.45)
Compliance & Auditability	(0.20, 0.25, 0.30)
Cost Efficiency	(0.35, 0.40, 0.45)
Implementation Complexity	(0.25, 0.30, 0.35)
Performance Reliability	(0.25, 0.30, 0.35)

3.2.2 Fuzzy TOPSIS methodology

Building on the FAHP-derived weights, the FTOPSIS method was applied to rank the Blockchain platform alternatives (F1, F2, and F3). The process involved constructing a fuzzy decision matrix representing the performance of each alternative under the selected criteria, followed by normalization and weighting of the matrix using the fuzzy weights obtained from the FAHP phase. Table 12 presents the weighted fuzzy decision matrix used to perform the FTOPSIS analysis.

The fuzzy evaluation matrices in Table 12 were derived by converting the same triangulated secondary data into linguistic categories and then into triangular fuzzy numbers following established MCDM literature.

Table 12. Defuzzified Decision Matrix for Blockchain Platforms.

Sub-Criteria	F1	F2	F3
Agility	0.70	0.60	0.60
Market Adoption	0.80	0.60	0.50
Vendor Support	0.80	0.70	0.60
Scalability	0.70	0.80	0.70
Interoperability	0.60	0.70	0.80
Security	0.90	0.80	0.70
Smart Contract Capabilities	0.70	0.80	0.70
Data Transparency	0.80	0.90	0.80
Compliance & Auditability	0.90	0.80	0.70
Cost Efficiency	0.60	0.80	0.90
Implementation Complexity	0.40	0.60	0.70
Performance Reliability	0.80	0.80	0.70

The fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) were determined for each criterion, and the distances of each alternative from these solutions were calculated using fuzzy Euclidean distance. The relative closeness (*Ri*) of each alternative to the FPIS was computed to determine the final ranking. Table 13 presents the results of the FTOPSIS analysis.

Table 13. Final Ranking of Blockchain Platforms using FAHP–FTOPSIS.

Alternative	Closeness Coefficient (*Ri*)	Rank
F1	0.451	2
F2	0.486	1
F3	0.394	3

The results from the FAHP–FTOPSIS method closely align with those obtained from the AHP–TOPSIS approach, with Alternative F2 consistently emerging as the most suitable blockchain platform, followed by F1 and F3. The consistent top ranking of F2 reflects its superior performance in scalability, interoperability, and data transparency, which are crucial for large-scale logistics networks that demand secure and efficient multi-stakeholder coordination. This result indicates that platforms adopting a hybrid blockchain architecture, that combines permissioned governance with public accessibility, tend to balance trust, transparency, and operational control more effectively than fully public or strictly private systems.

From a managerial perspective, this finding suggests that logistics firms should prioritize blockchain solutions that can integrate seamlessly with existing ERP or IoT infrastructures, while ensuring regulatory compliance and auditability. The developed decision framework can serve as a practical decision-support tool: managers can apply their own strategic weightings to replicate the ranking process and tailor platform selection to their specific operational priorities. For instance, firms emphasizing interoperability and real-time visibility may favor F2-type systems, whereas those seeking cost efficiency or ease of deployment may lean toward F3-type alternatives.

The insights also extend beyond logistics. In healthcare supply chains, where regulatory auditability and data integrity dominate, F1-like platforms could be more appropriate. In food and cold-chain logistics, transparency and traceability remain paramount, reaffirming the advantage of F2-type configurations. Conversely, in manufacturing or retail, scalability and cost factors may elevate F3-like solutions. These variations confirm that the proposed framework is adaptable across industries, offering decision-makers a structured and repeatable approach for evaluating emerging blockchain solutions under both certain and uncertain conditions.

4. Limitations and future research directions

While this study proposes a comprehensive MCDM framework for choosing Blockchain platforms in supply chains, several limitations exist. First, computational complexity is significant. As criteria and alternatives multiply, AHP and TOPSIS become resource-intensive, and AHP consistency checks escalate exponentially (Govindan et al., 2015). Fuzzy variants (FAHP, FTOPSIS) add further overhead. Future work should develop faster algorithms or approximations that shorten runtime without harming decision quality.

Second, data availability remains critical. MCDM accuracy depends on reliable expert assessments and performance metrics (Baydaş et al., 2022), yet platform documentation, adoption, and transparency vary widely, weakening objectivity. Fuzzy logic mitigates imprecision but still needs a sound data baseline. Enriching inputs with empirical benchmarks, longitudinal case studies, telemetry, and user feedback is recommended.

Third, the framework is domain-specific. Criteria weights and the evaluation hierarchy are tailored to logistics, enhancing relevance but limiting generalisability. Adapting the model to energy, public-service, or healthcare contexts, where blockchain requirements and criteria differ, would extend its reach.

Another limitation concerns empirical validation. Although the evaluation parameters were derived from real platform data and expert judgment, the analysis did not include direct field testing or case-study implementation. Future research should complement the comparative framework with industry-specific case studies or user surveys to capture contextual factors such as organizational readiness, regulatory constraints, and integration costs. Incorporating primary empirical evidence will further substantiate the framework's practical applicability and refine weight calibrations for different logistics domains.

Finally, subjectivity endures. Weight derivation relies on expert judgment, introducing bias and variability (Mardani et al., 2015). Although fuzzy methods temper uncertainty, judgment still dominates. Integrating Delphi rounds or machine-learning-assisted scoring could yield more objective evaluations (Biju Patnaik University of Technology (BPUT), Rourkela, Odisha, India et al., 2023).

In sum, while the framework offers a structured approach to intelligent-logistics blockchain selection, addressing computational, empirical, contextual, and cognitive limits will enhance accuracy, scalability, and applicability. Future studies should pursue algorithmic streamlining, richer datasets, cross-domain tests, and hybrid human-machine decision models.

5. Conclusion

This study introduced an integrated decision-making framework for evaluating and selecting Blockchain platforms within intelligent logistic ecosystems by combining AHP–TOPSIS and FAHP–FTOPSIS methodologies. The approach offers a rigorous and structured means of comparing real-world Blockchain platforms based on a diverse set of criteria that reflect business priorities, technical capabilities, platform functionalities, and operational impacts. The use of AHP enabled the derivation of clear and consistent criteria weights, while TOPSIS provided a logical method for ranking alternatives. In parallel, the FAHP–FTOPSIS framework incorporated expert uncertainty, improving the model's ability to handle imprecision and ambiguity in decision-making.

The results demonstrated a high level of coherence between both methodologies, reinforcing the validity of the selected platform and the overall evaluation model. The hybrid MCDM approach not only supports more reliable decision-making but also contributes to strategic alignment by ensuring that technology selection is grounded in well-defined logistical and operational needs. Nonetheless, the study recognizes some limitations, particularly in terms of subjective input, data dependency, and contextual applicability to the logistics sector only.

Looking ahead, future research could explore the integration of real-time performance monitoring data into the decision framework, enabling continuous re-evaluation of Blockchain platforms as they evolve or undergo updates. Another promising avenue would be to combine this MCDM approach with Blockchain simulation environments or digital twins, allowing decision-makers to validate the theoretical rankings through simulated operational scenarios. Additionally, research could investigate multi-stakeholder decision models, incorporating conflicting preferences from different actors in the supply chain to derive more balanced and consensual outcomes. Developing interactive decision-support systems or dashboards based on this framework could also facilitate practical implementation and enhance usability for logistics managers and strategic planners. Finally, longitudinal studies tracking the post-selection impact of chosen Blockchain platforms could offer valuable feedback loops for refining future decision-making criteria and methodologies.

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