

Explainable Multi-Criteria Decision Analysis for Supply Chain Risk Management: An Integrated FRAM-AHP-XAI Framework with Theoretical Foundations

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Abstract: Supply chain decision-making under uncertainty requires integrating quantitative risk assessment with interpretable artificial intelligence. This paper extends the FRAM-AHP (Functional Resonance Analysis Method - Analytical Hierarchy Process) framework by embedding explainable AI (XAI) techniques to enhance transparency in multi-criteria risk prioritization. We introduce a theoretical foundation through a novel theorem establishing how functional variability propagates through decision hierarchies, along with a formal proposition on AI-augmented optimization strategies. Our framework combines MCDA principles with machine learning interpretability (LIME and SHAP) to ensure decision transparency for supply chain managers. We demonstrate that integrating functional resonance theory with explainable decision models reduces decision bias by quantifying the impact of operational variability on risk priorities. Computational experiments on real supply chain datasets show that the framework achieves 27% improvement in decision consistency while maintaining full interpretability.

Key-Words: Explainable AI, Multi-Criteria Decision Analysis, Supply Chain Risk Management, FRAM, AHP, SHAP, Trustworthy AI, Functional Resonance

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1 Introduction

Modern supply chains operate in increasingly uncertain environments characterized by global interconnectedness, regulatory complexity, and technological disruption, [1], [2], [3]. Supply chain risk management has evolved significantly over the past two decades, with researchers emphasizing the need for systematic approaches to identify, assess, and mitigate disruption risks, [4], [5]. Recent global events, including the COVID-19 pandemic, have further highlighted the importance of building resilient and viable supply chains, [6], while the emergence of Industry 4.0 technologies has transformed supply chain operations, [7]. Traditional risk management approaches often fail to capture the non-linear dynamics of systemic failures and the cascading effects of operational variability [8]. The analytical hierarchy process (AHP) [9] provides structured multi-criteria decision-making but lacks mechanisms to account for complex functional interactions. Extensions of AHP, including its integration with fuzzy logic, [10], [11], and combination with other MCDA methods such as TOPSIS, [12], have been widely applied in supply chain contexts. Modified failure mode and effects analysis approaches have also been employed to evaluate supply chain risks, [13], while Monte Carlo sim-

ulation techniques provide quantitative risk assessment capabilities, [14]. The Functional Resonance Analysis Method (FRAM) addresses the limitation of static approaches by modeling how small variations in system functions can amplify to create systemic risks, [15].

However, existing FRAM-AHP implementations face a critical limitation: they do not provide decision-makers with interpretable explanations of *why* certain risk priorities emerge. This is particularly problematic in regulated industries and organizations pursuing trustworthy AI adoption. Decision-makers need not only to know the priority ranking but to understand the contribution of each variable and how functional variability influences this ranking, [16].

This paper addresses this gap by integrating explainable artificial intelligence (XAI) techniques into the FRAM-AHP framework. We contribute:

1. A formal theoretical framework establishing how functional variability impacts decision hierarchies (Theorem 1);
2. A proposition on optimal AI-augmented decision strategies under uncertainty (Proposition 1);
3. An implementation combining MCDA with

model-agnostic interpretability methods (LIME, SHAP);

- Empirical validation showing improved decision consistency and transparency.

This work bridges the gap between black-box AI predictions and transparent MCDA, enabling organizations to implement trustworthy AI in supply chain risk management.

2 Theoretical Framework

2.1 Decision Hierarchy and Functional

Variability

Let $H = (L_0, L_1, \dots, L_n)$ denote a decision hierarchy with levels L_i where L_0 is the goal, L_n contains alternatives, and intermediate levels contain criteria, [17]. Let $w_j^{(i)}$ denote the priority weight of criterion j at level i , computed via AHP pairwise comparisons.

For each criterion, we associate a critical function $F_j = (I_j, O_j, P_j, R_j, C_j, T_j)$ from FRAM analysis, where variability is measured as $\sigma_j \in [0, 1]$, with 0 representing stable performance and 1 representing high variability.

Definition 1 (Functional Resonance Impact). *The functional resonance impact of criterion j is defined in Equation (1):*

$$FRI_j = \sigma_j \cdot \mathcal{A}(F_j) \quad (1)$$

where $\mathcal{A}(F_j)$ is the adjacency impact measure representing how function F_j propagates variability to dependent functions.

2.2 Main Theoretical Result

Theorem 2 (Variability-Adjusted Priority Propagation). *Let $\mathbf{w} = (w_1, \dots, w_m)$ be the priority vector from AHP for m criteria, and let $\boldsymbol{\sigma} = (\sigma_1, \dots, \sigma_m)$ be the functional variability vector from FRAM analysis. Define the adjusted priority vector $\mathbf{w}^* = (w_1^*, \dots, w_m^*)$ where, as shown in Equation (2):*

$$w_j^* = w_j \cdot (1 + \alpha \cdot \sigma_j), \quad j = 1, \dots, m \quad (2)$$

with normalization $\sum_{j=1}^m w_j^* = 1$, and $\alpha > 0$ is a sensitivity parameter. Then, for any two alternatives A_i and A_k with scores $\mathbf{r}_i = (r_{i1}, \dots, r_{im})$ and $\mathbf{r}_k = (r_{k1}, \dots, r_{km})$, the ranking difference satisfies Equation (3):

$$|R_i^* - R_k^*| - |R_i - R_k| \leq \alpha \sum_{j=1}^m \sigma_j |r_{ij} - r_{kj}| \quad (3)$$

where $R_i = \sum_{j=1}^m w_j r_{ij}$ and $R_k^* = \sum_{j=1}^m w_j^* r_{kj}$.

Proof. We have, as shown in Equation (4):

$$\begin{aligned} R_i^* - R_k^* &= \sum_{j=1}^m w_j^* r_{ij} - \sum_{j=1}^m w_j^* r_{kj} \\ &= \sum_{j=1}^m w_j (1 + \alpha \sigma_j) (r_{ij} - r_{kj}) \\ &= (R_i - R_k) + \alpha \sum_{j=1}^m w_j \sigma_j (r_{ij} - r_{kj}) \end{aligned} \quad (4)$$

By triangle inequality, as expressed in Equation (5):

$$\begin{aligned} |R_i^* - R_k^*| - |R_i - R_k| &\leq \left| \alpha \sum_{j=1}^m w_j \sigma_j (r_{ij} - r_{kj}) \right| \\ &\leq \alpha \sum_{j=1}^m w_j \sigma_j |r_{ij} - r_{kj}| \\ &\leq \alpha \sum_{j=1}^m \sigma_j |r_{ij} - r_{kj}| \end{aligned} \quad (5)$$

where the last inequality uses $w_j \leq 1$ and $\sum_{j=1}^m w_j = 1$. \square

2.3 Interpretation and Implications

Theorem 1 provides theoretical grounding for integrating operational variability into multi-criteria decisions. The bound establishes that variability-induced ranking changes are proportional to both the variability levels σ_j and the differences in criterion scores. This formalization enables supply chain managers to:

- Quantify the maximum possible ranking perturbation due to functional variability;
- Calibrate the sensitivity parameter α based on organizational risk tolerance;
- Identify criteria where variability control yields greatest decision stability.

3 XAI Integration and Trustworthiness

3.1 Explainable AI Techniques

Modern machine learning models can predict supply chain risks effectively but lack interpretability. We employ two complementary XAI methods:

LIME (Local Interpretable Model-agnostic Explanations), [18]: For prediction $f(x)$ at instance x ,

LIME approximates f locally by a linear model g minimizing Equation (6):

$$\mathcal{L}(f, g, \pi_x) = \sum_{z \in \mathcal{Z}} \pi_x(z) [f(z) - g(z)]^2 \quad (6)$$

where π_x is a proximity measure and \mathcal{Z} is a set of perturbed samples near x .

SHAP (SHapley Additive exPlanations), [19]: Based on cooperative game theory, SHAP values ϕ_i for feature i satisfy Equation (7):

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N| - |S| - 1)!}{|N|!} [f(S \cup \{i\}) - f(S)] \quad (7)$$

These values satisfy the efficiency property: $\sum_{i=1}^n \phi_i = f(x) - f(\emptyset)$.

3.2 Proposition on Trustworthy AI-MCDA

Proposition 3 (Optimal AI-Augmented Decision Strategy). *An AI-augmented MCDA system achieves trustworthy decision-making if the following conditions hold:*

(C1) Explainability Sufficiency: *The SHAP explainability ratio satisfies Equation (8):*

$$\rho_{SHAP} = 1 - R_{SHAP}^2 < 0.15 \quad (8)$$

(C2) Multi-Method Consistency: *For top- k features, LIME and SHAP agree with probability $p > 0.90$, as stated in Equation (9):*

$$P(\text{Top-}k_{LIME} = \text{Top-}k_{SHAP}) > 0.90 \quad (9)$$

(C3) Decision Alignment: *Adjusted weights \mathbf{w}^* correlate with aggregated SHAP importance, as expressed in Equation (10):*

$$\text{corr}(\mathbf{w}^*, \bar{\phi}) > 0.80 \quad (10)$$

where $\bar{\phi}_j = \mathbb{E}[|\phi_j|]$ across instances.

Rationale. Condition C1 ensures SHAP captures $> 85\%$ of prediction variance, C2 guarantees robustness across explanation methods, and C3 aligns MCDA weights with learned feature importance. Together, these criteria establish that AI-augmented decisions are transparent, consistent, and theoretically justified.

3.3 Framework Architecture

The integrated FRAM-AHP-XAI framework operates through the following pipeline:

1. **FRAM Analysis:** Identify critical functions and measure variability σ_j for each;

2. **AHP Weights:** Conduct pairwise comparisons to obtain base weights w_j ;
3. **Theorem 1 Adjustment:** Apply variability adjustment to get w_j^* ;
4. **ML Training:** Train models with features weighted by w_j^* ;
5. **XAI Analysis:** Compute SHAP and LIME explanations for predictions;
6. **Validation:** Verify Proposition 1 criteria (C1–C3);
7. **Decision Output:** Provide rankings with feature-level explanations.

This architecture ensures decisions are not only accurate but also interpretable and aligned with domain expertise encoded in FRAM-AHP.

4 Computational Implementation

4.1 Algorithm Description

The computational workflow of the FRAM-AHP-XAI decision framework is presented in Table 1, which describes the step-by-step procedure for integrating functional variability analysis with explainable AI techniques.

Table 1: FRAM-AHP-XAI Framework Algorithm

| Step | Description |
|---|---|
| Input: Data \mathcal{D} , criteria \mathcal{C} | |
| Output: Ranked alternatives | |
| 1 | FRAM analysis: extract $\{\sigma_j\}$ |
| 2 | AHP comparisons: compute $\{w_j\}$ |
| 3 | Theorem 1: $w_j^* \leftarrow w_j(1 + \alpha\sigma_j)$ |
| 4 | Train ML model $f_{\mathbf{w}^*}$ |
| 5 | For each $x_i \in \mathcal{D}$: |
| 5a | Predict: $y_i = f_{\mathbf{w}^*}(x_i)$ |
| 5b | SHAP values: $\{\phi_{ij}\}$ |
| 5c | LIME: $\{l_{ij}\}$ |
| 6 | Verify Prop. 1 (C1–C3) |
| 7 | Rank by $\{y_i\}$ |
| 8 | Return rankings, $\{\phi_{ij}\}$ |

Legend: σ_j = variability; w_j = AHP weight; w_j^* = adjusted weight; ϕ_{ij} = SHAP value.

Source: created by the authors.

4.2 Complexity Analysis

The computational complexity is dominated by:

- AHP: $O(m^2 n_c)$ for m criteria and n_c comparisons;
- ML training: $O(n_s m \log m)$ for n_s samples (typical ensemble);

- SHAP computation: $O(n_a m 2^m)$ exact, or $O(n_a m T)$ for T samples;
- Total: $O(n_a m T + n_s m \log m)$ for practical implementations.

For supply chains with $m \approx 10\text{--}20$ criteria and $n_a \approx 100$ alternatives, computation time remains under 5 minutes on standard hardware.

5 Experimental Results

5.1 Dataset and Evaluation Metrics

We evaluated the framework on 200 supply chain risk scenarios from manufacturing, logistics, and distribution networks. Each scenario comprises:

- 12–18 risk criteria (demand volatility, supplier reliability, transportation costs, regulatory compliance, etc.);
- 50–100 alternative mitigation strategies;
- Historical performance data spanning 3–5 years.

Metrics:

- **Decision Consistency:** AHP consistency ratio (CR)
- **Explainability:** SHAP ratio ρ_{SHAP}
- **Agreement:** LIME-SHAP top-3 concordance
- **Efficiency:** Decision time (hours)
- **Trust:** Stakeholder confidence (survey-based)

5.2 Key Findings

Decision Consistency Improvement: Traditional AHP without FRAM adjustment yielded mean CR = 0.152 across scenarios, indicating marginal consistency. Integrating FRAM variability adjustment (Theorem 1) reduced this to CR = 0.112, a 27% improvement. This enhancement reflects better alignment between expert judgments and operational realities captured by functional variability analysis.

Explainability Performance: The SHAP explainability ratio averaged $\rho_{\text{SHAP}} = 0.089$ ($R_{\text{SHAP}}^2 = 0.911$), well below the 0.15 threshold in Proposition 1 (C1). LIME-SHAP agreement on top-3 features reached 94%, exceeding the 90% criterion (C2). Decision-SHAP correlation met threshold (C3) in 98% of scenarios, with only 2 outlier cases featuring unusual risk structures.

Practical Impact: Average decision time decreased from 4.5 hours (manual sensitivity analysis) to 2.1 hours (automated SHAP), a 53% reduction. Stakeholder confidence improved from 62% to 89% when explanations were provided alongside rankings, demonstrating that interpretability significantly enhances acceptance.

5.3 Comparison with Baselines

Table 2 summarizes performance against baseline methods.

Table 2: Decision Methods: a comparison

| Method | CR | ρ_{SHAP} | Time (h) |
|-----------------|--------------|----------------------|------------|
| Traditional AHP | 0.152 | — | 4.5 |
| FRAM-AHP | 0.118 | — | 3.8 |
| Black-box ML | — | 0.241 | 1.2 |
| FRAM-AHP-XAI | 0.112 | 0.089 | 2.1 |

Legend: CR = consistency ratio; ρ_{SHAP} = SHAP explainability ratio; Time = average decision time in hours.

Source: created by the authors.

The integrated framework achieves best-in-class performance across consistency, explainability, and efficiency dimensions.

6 Discussion

6.1 Theoretical Contributions

The theoretical framework developed in this paper, formalized through Equations (1)–(10), provides a rigorous foundation for integrating operational variability into multi-criteria decisions. Theorem 1 formalizes the intuition that operational variability should adjust priority weights, providing a bounded adjustment mechanism: $\Delta R \leq \alpha \sum_j \sigma_j \cdot r_j$. This bound quantifies permissible decision modifications and enables systematic risk prioritization.

Proposition 1 connects explainability directly to decision trustworthiness, establishing concrete conditions (C1–C3) for AI adoption in MCDA. The requirement that SHAP-based explanations align with decision weights ensures transparency without sacrificing model sophistication.

6.2 Practical Implications

Organizations can implement transparent, auditable supply chain risk decisions without sacrificing analytical power. The framework’s modularity allows substitution of different MCDA methods (TOPSIS, ELECTRE) or ML models, provided XAI analysis is applied consistently.

The 27% consistency improvement and 53% time reduction translate directly to operational benefits: faster response to supply disruptions, better resource allocation, and higher stakeholder buy-in for risk mitigation initiatives.

6.3 Limitations and Future Work

Current implementation assumes independence between criteria—extension to hierarchical correlations

is underway. The framework's sensitivity to α calibration requires further investigation of optimal selection mechanisms. Future work should explore:

- Dynamic scenarios where variability changes over time, requiring adaptive weight adjustments;
- Integration with reinforcement learning for sequential decision-making in supply chains;
- Extension to multi-objective optimization with competing risk/cost/resilience trade-offs;
- Real-time monitoring systems that update FRAM variability assessments continuously.

7 Conclusion

This paper bridges theoretical gaps in MCDA and practical needs in supply chain risk management. By combining FRAM's functional perspective with AHP's hierarchical structure and XAI's interpretability requirements, we provide supply chain managers with transparent, theoretically justified, and practically implementable decision tools.

The novel theorem establishes how variability propagates through decision hierarchies, while the proposition provides concrete conditions for trustworthy AI-augmented decisions. Empirical validation demonstrates significant improvements in decision consistency (27%), efficiency (53% time reduction), and stakeholder confidence (from 62% to 89%).

As organizations increasingly adopt AI for critical operational decisions, the framework's emphasis on explainability and theoretical rigor positions it as a model for trustworthy AI in supply chain management and beyond. Future extensions to dynamic environments and multi-objective settings promise broader applicability across diverse operational contexts.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Massimiliano Ferrara conceived the theoretical framework, developed Theorem 1 and Proposition 1, supervised the research, and wrote the theoretical sections.

Valeria Isgrò implemented the computational framework, conducted experiments, performed data analysis, and drafted the implementation and results sections.

Both authors contributed to the manuscript revision and approved the final version.

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Conflicts of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

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