An AI Implementation for Risk Analysis in Supply Chains 4.0: A Multicriteria Model for Sustainability and Resilience

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Abstract

Modern supply chains, increasingly complex and interconnected, demand advanced risk management. This study proposes an integrated FRAM-AHP approach: Functional Resonance Analysis Method (FRAM) analyses systemic interactions that generate operational variability, while Analytical Hierarchy Process (AHP) enables risk prioritisation through multicriteria evaluation. The combination provides a holistic and structured perspective, enhancing the resilience and sustainability of supply chains in uncertain and highly variable global contexts.

Keywords

Multicriteria decision making, Risk Assessment, FRAM/AHP Method, Supply chain.

1. Introduction

Supply chains are vital to global economic systems, facilitating the smooth flow of goods and services. However, increasing complexity—fueled by globalisation, technological advancements, and interconnected networks—has heightened their vulnerability to diverse risks (Chopra and Sodhi [1]). These include supply disruptions, demand volatility, natural hazards, geopolitical issues, and financial instability (Fan and Stevenson [2]). Addressing such challenges requires effective risk management, with risk assessment playing a pivotal role. This involves identifying, analysing, and prioritising potential threats based on their probability and consequences (Manuj and Mentzer [3]). Among the tools developed for this purpose, the FRAM-AHP approach stands out for its integrative capabilities. The Functional Resonance Analysis Method (FRAM) helps uncover how variability in system functions can lead to unexpected outcomes (Hollnagel [4]), while the Analytic Hierarchy Process (AHP) aids in systematically ranking risks using both subjective and objective data (Saaty [5]). This paper investigates the FRAM-AHP framework's practical application, highlighting its strengths, limitations, and future relevance in supply chain risk analysis.

2. Literature Review

In an increasingly unstable global context, supply chain risk management (SCRM) is an essential strategic component. Chopra and Sodhi [1] define SCRM as the process aimed at identifying, assessing and mitigating risks that may compromise supply chain performance. Such risks include operational, strategic, financial and environmental events (Kleindorfer and Saad [6]). Several studies underline the need for a proactive approach to risk management. Manuj and Mentzer [3] highlight the importance for companies to adopt tools capable of anticipating and promptly addressing disruptions. In line with this perspective, Radivojević and Gajović [7] propose systematic risk assessment and prioritization models based on multi-criteria decision-making methods, such as the AHP, which allow for the integration of

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qualitative and quantitative aspects. One of the main challenges in SCRM is the quantification of risks, often characterized by uncertainty and complex interconnections. To address these critical issues, the literature proposes different tools. Among the qualitative methods, the Failure Mode and Effect Analysis (FMEA) allows to identify potential failure points and assess their probability and impacts. However, it has limitations in the analysis of complex dynamics, especially in uncertain contexts such as the COVID-19 pandemic (Ghadir et al. [8]). Among the quantitative approaches, Monte Carlo simulations generate stochastic scenarios useful for estimating the impact of risks. This method takes uncertainty into account, but requires significant computational resources and high-quality data (Schmitt and Singh [9]). To overcome the limitations of traditional methods, hybrid approaches such as the FRAM-AHP method have been developed. The FRAM, introduced by Hollnagel [4], allows to analyze functional interactions between activities, showing how minimal variations can generate cascade effects. In the supply chain, this allows us to understand how a delay by a supplier can affect other aspects, such as inventory or customer satisfaction. The AHP, developed by Saaty [5], allows us to hierarchically structure decision criteria and compare them in pairs to establish priorities, which is useful in classifying risks according to probability, impact and effectiveness of strategies (Ganguly and Kumar [10]; Salehi Heidari et al. [11]). With the advent of Supply Chain 4.0, digital technologies and cyber-physical systems have transformed risk management, increasing complexity but also predictive capacity and traceability (Frederico et al. [12]). Garay-Rondero et al. [13] highlight how digital models improve real-time monitoring. In this direction, Barilla et al. [14] propose an integrated cost-benefit model, based on tax data and Industry 4.0 tax credits, to support strategic planning. The FRAM-AHP method stands out for its ability to analyze both the systemic and dynamic dimension of risk, as well as the evaluative and decisional one, offering an integrated and effective approach to strengthen the resilience, efficiency and sustainability of supply chains

3. Methodology

Integrating the FRAM with AHP provides an effective framework for risk assessment in supply chain management, especially in complex and uncertain economic environments. Risk management requires methods combining qualitative and quantitative perspectives: AHP structures complex decisions by organizing multi-criteria assessments, while FRAM models the interactions within the system, offering deeper insight into supply chain behavior and resilience. This combination allows for comprehensive analysis, aiding in identifying critical vulnerabilities, strategic planning, resource allocation, and improving responses to disruptions. AHP's key feature is creating a decision hierarchy, dividing the problem into objectives, criteria, sub-criteria, and alternatives. These components are linked to ensure consistent comparisons, maintaining independence among elements at the same level and dependence between adjacent levels. According to Saaty [5], the process begins from the general objective and proceeds to alternatives, ensuring a clear, structured decision-making process. After defining the hierarchy, it is necessary to identify the relevant alternatives through careful analysis. Information for this phase is collected through pairwise comparisons of the alternatives, based on the criteria of the hierarchy, and the judgment of experts who evaluate the relative importance with a qualitative scale, for example from "equal importance" to "extremely important". The process of collecting opinions can be supported by a specially designed form, as shown in the following example:

Table 1
Example: Importance Comparison Between A and B

A							x		**B**
	Extremely strong	Very strong	**Strong**	Marginally strong	Equal importance	Marginally strong	**Strong**	Very strong	

In the example, the symbol "X" indicates that, according to the reference criterion, alternative B is very important compared to alternative A. This type of comparison allows for a systematic and conscious evaluation, which contributes to the coherence and precision of the decision-making process. To perform comparisons, it is essential to use a numerical scale that allows quantifying how dominant an alternative is compared to another according to a given evaluation criterion. The AHP method uses a specific scale (Table 2), composed of 9 levels of judgment, which facilitates the achievement of more coherent and linear decisions.

Table 2
Fundamental scale for pairwise comparison

Numeric value	Judgement	Interpretation
1	Equal importance	Two activities contribute equally
3	Marginally strong	Experience and judgement slightly favour one activity over another
5	Strong	Experience and judgement strongly favour one activity over another.
7	Very strong	Experience and judgement strongly favour one activity over another; its dominance is demonstrated in practice
9	Extremely strong	Evidence favours one activity over another with the highest possible order of affirmation
2-4-6-8	Intermediate ratings	They are assigned as compromise measures

The total number of comparisons needed depends on the amount of elements to be analyzed and can be calculated with the formula:

$$\frac{n(n-1)}{2} \tag{1}$$

where n is the number of elements to be compared.
According to Saaty and Vargas [15], comparisons with pairs of criteria are arranged in a square matrix, where each element a_ij represents the comparison value between the criterion of row *'i'* and that of column *'j'*. The elements of the main diagonal of the matrix are equal to 1, since each element compared with itself is always equivalent. If an element of the column is preferred to that of the row, the reciprocal value of the comparison is inserted into the matrix, indicating that the element of the row is relatively less important than that of the column. Conversely, if the element of the row is preferred, the numerical value corresponding to the Saaty scale is inserted. The matrix will have this structure:

$$M = \begin{pmatrix} 1 & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ \frac{1}{a_{1n}} & \cdots & 1 \end{pmatrix}$$

After constructing the comparison matrix, the relative weights of each element are determined. This is done by calculating the partial values for each criterion $v_i\,(A_j)$, where *j* varies from 1 to n. These values, known as relative impacts, reflect the subjective judgments provided by experts on the various elements and are normalized using the formula:

$$\sum_{i=1}^{n} v_i\,(A_j) = 1 \quad con\; j = 1,,,n$$

Where n is the number of alternatives or elements compared. Each part of this sum consists of:

$$v_j(A_j) = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \quad con\; j = 1,,,n$$

This causes the vector of priorities of alternative *'i'*, in relation to the importance criterion factor, to be defined by the following equation:

$$v_k = (A_i) = \sum_{j=1}^{n} \frac{v_j\,(A_i)}{n} \quad con\ i = 1, \ldots, n$$

To determine the weight of each factor, it is necessary to add the values of each element a_{ij} for each column of the matrix "M". Next, a new normalized matrix, called "MRW", is constructed. Each element a_{ij} of the matrix "MRW" represents the relative weight of each element of the column compared to the elements of the upper row. Normalization is obtained by dividing each element of the matrix *'M'* by the sum of the values of its respective column. Finally, the weighted average of the elements of each row of the matrix "MRW" returns the relative weight of each element in the original matrix *'M'*. This process ensures that the relative weights are calculated consistently and accurately reflect the expressed preferences. To ensure the reliability of the evaluations performed, the AHP method includes a consistency analysis of the processed data. Since the matrix *'M'* is reciprocal, if all the evaluations expressed by the experts were perfectly consistent, it would be possible to verify the relationship:

$$a_{ij} \times a_{jk} = a_{ik} \quad \forall i, j, k$$

In this case, the matrix *"M"* would be completely coherent. Considering n as the number of elements,λ_{max} as the maximum eigenvalue of the matrix *"M"* and *"w"* as the priority vector, it can be stated that, if the experts' judgments are coherent, then:

$$\lambda_{max} = n\ and\ a_{ij} = \frac{w_i}{w_j}$$

However, since some inconsistency is unavoidable, it is measured by observing that the closer λ_{max} is to N, the greater the consistency of the evaluations. Saaty [16] has shown that, for a matrix M, one can determine a vector that satisfies the equation: $A_w = \lambda_{max} x$ *'w'*, and to calculate the maximum eigenvalue (λ_{max}), the following formula is used:

$$\lambda_{max} = \frac{1}{n} \sum_{I=1}^{N} v_i \frac{[A_w]_i}{w_j}$$

It should be noted that marginal variations in terms of a_{ij} imply marginal variations in λ_{max} where the deviation of the eigenvector with respect to n (order number of the matrix) is considered a measure of coherence. It can therefore be stated that λ_{max} allows us to evaluate the proximity of the scale developed by Basak and Saaty [17] with the scale of relations and quotients that would be used if the matrix *"M"* were totally coherent. This can be done using a coherence index (CI). According to Saaty's theorem, *"M"* is coherent if and only if, $\lambda_{max} \geq n$. That is, if the matrix *"M"* is coherent, then we calculate the amount of disturbance of the matrix *"M"* using the relation:

$$CI = \frac{(\lambda_{max} - n)}{(n-1)}$$

The reference index CI, will have a value less than 0.1 (Saaty and Vargas [15]). Considering these problems related to the consistency of the matrix data, Saaty proposes to calculate a consistency relation (CR), obtained with the equation:

$$CR = \frac{CI}{RI}$$

Where CI corresponds to the coherence index calculated using the above-mentioned equation. The RI element is a random coherence index, calculated for square matrices of order n by Oak Ridge National Laboratory – USA., presented in Table 2 (Saaty and Vargas [15]).

Table 3
Random consistency index

N	1	2	3	4	5	6	7	8	9	10
Random consistency index (R.I.)	0	0	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49

In the AHP, the Consistency Ratio (CR) indicates the coherence of pairwise comparisons. A CR value of zero is expected when the number of elements (n) is 1 or 2. For n = 3, the CR should be under 0.05, and for n = 4, below 0.08. Generally, for matrices where n > 4, a CR of 0.10 or less is considered acceptable. If the CR exceeds these limits, it suggests a need to revisit the judgements with the decision maker to uncover possible sources of inconsistency, potentially requiring a revision of the original evaluations. A CR above 10% reflects complexity or anomalies that challenge consistent decision-making. Overall, AHP tolerates a consistency index up to 10% across the full hierarchy, as inconsistencies within this margin are minor compared to the significance of the derived eigenvector.The FRAM, developed by Hollnagel [4], is used to examine complex systems from a systemic perspective. Unlike deterministic models, FRAM accounts for non-linear interactions and the amplification of normal operational variability, which can yield both beneficial and adverse outcomes. The model is represented through the following function:

$$F_i = (I_i, O_i, P_i, R_i, C_i, T_i)$$

and described by six fundamental elements:

- Input (I): the information or resources needed to initiate the function;
- Output (O): the result or product of the function;
- Preconditions (P): conditions that must be met for the function to begin;
- Resource (R): materials, tools, or other resources needed for the function;
- Control (C): mechanisms that guide or regulate the function;
- Time (T): time constraints or deadlines associated with the function,

Where F_i is the function and the six elements $I_i, O_i, P_i, R_i, C_i, T_i$ define its characteristics. The interactions between the functions are modeled as a complex network, often visualized using adjacency graphs or matrices. These interactions reveal how variability in performance in a function can propagate through the system, potentially creating the conditions for functional resonance.
The FRAM/AHP mixed model combines the strengths of AHP, used for risk assessment and prioritization, and FRAM, which allows to analyse the complexity of interactions between critical supply chain functions. This integration allows a deeper understanding of risk, considering both the priorities of each criterion and the non-linear interactions and operational variabilities. The mixed model assesses risk in the supply chain by analyzing both risk hierarchies (AHP method) and their critical functional interactions (FRAM approach). This approach helps to decompose the problem into a hierarchy of criteria and sub-criteria, integrating the functional connections that can amplify or mitigate risks.

3.1. Structuring of the mixed FRAM/AHP model

1. Main objective:
    - Risk assessment in the supply chain.
2. Main criteria (from AHP):

Table 4
Main criteria

Supply risk	Logistics risk	Demand risk	Geopolitical risk	Environmental risk
Supplier reliability	Carrier reliability	Demand forecasting	Political instability in supplier countries	Political instability in supplier countries
Lead times	Warehouse capacity	Unpredictability of demand	Import/export restrictions	Import/export restrictions
Product quality	Transportation delays	Information distortion	Economic sanctions	Economic sanctions

3.2. Functional analysis (from FRAM):

Identification of critical functions associated with each criterion, which represent the main operational processes of the supply chain. The functions will be evaluated in terms of:

- Input (what is needed to start a function).
- Output (results generated).
- Controls (mechanisms that influence the function).
- Resources (tools or capabilities required).
- Time (synchronization of functions).

4. Results

To assess the relative significance of various supply chain risks, we applied the AHP, constructing pairwise comparison matrices based on Saaty's 1–9 scale [15] (Table 2). This method enables structured evaluation, where 1 denotes equal importance and 9 indicates extreme preference of one factor over another. The number of necessary comparisons follows the formula *n*, $\frac{n(n-1)}{2}$. We examined five primary risk categories: environmental, geopolitical, demand, logistics, and supply risks. Expert judgements and existing studies guided our assignment of comparison values. For instance, environmental risks were rated significantly higher than logistics risks (score = 7), reflecting increasing climate-related disruptions, as emphasised by Ivanov [18]. Geopolitical risks were prioritised over demand risks, consistent with Ghadge et al. [19], who stress the severe consequences of political instability. Demand risks were considered more critical than logistics risks, aligning with Chopra and Sodhi [1], who underscore the challenges of fluctuating customer demand in global networks. These informed evaluations helped reduce subjectivity and ensured that our risk prioritisation was grounded in both expert insights and literature evidence.

Table 5
Pairwise comparison matrix

-	Environmental risk	Geopolitical risk	Demand risk	Logistics risk	Supply risk
Environmental risk	1	3	5	7	9
Geopolitical risk	1/3	1	3	5	7
Demand risk	1/5	1/3	1	5	5
Logistics risk	1/7	1/5	1/5	1	3
Supply risk	1/9	1/7	1/5	1/3	1

Adding the values of the individual columns:

- Environmental risk 1.79;

- Geopolitical risk 4.68;
- Demand risk 9.40;
- Logistics risk 18.33;
- Supply risk 25.00.

and normalizing the matrix (we divide each element by the sum of the column):

Table 6
Normalised matrix

-	Environmental risk	Geopolitical risk	Demand risk	Logistics risk	Supply risk
Environmental risk	0,56	0,64	0,53	0,38	0,36
Geopolitical risk	0,19	0,21	0,32	0,27	0,28
Demand risk	0,11	0,07	0,11	0,27	0,20
Logistics risk	0,08	0,04	0,02	0,05	0,12
Supply risk	0,06	0,03	0,02	0,02	0,04

we can calculate the relative weight for each risk (average of the values for each row):

- $$Environmental : \frac{0.56 + 0.64 + 0.53 + 0.38 + 0.36}{5} = 0.495 \quad (49.50\%);$$
- $$Geopolitical : \frac{0.19 + 0.21 + 0.032 + 0.27 + 0.28}{5} = 0.2544 \quad (25.44\%);$$
- $$Demand : \frac{0.11 + 0.07 + 0.11 + 0.27 + 0.20}{5} = 0.1525 \quad (15.25\%);$$
- $$Logistics : \frac{0.08 + 0.04 + 0.02 + 0.05 + 0.12}{5} = 0.0637 \quad (6.37\%);$$
- $$Supply : \frac{0.06 + 0.03 + 0.02 + 0.02 + 0.04}{5} = 0.0344 \quad (3.44\%),$$

and we calculate the vector of weighted sums:

- $V_1 = (1 \cdot 0.495) + (3 \cdot 0.2544) + (5 \cdot 0.1525) + (7 \cdot 0.0637) + (9 \cdot 0.0344) = 2.776431$
- $V_2 = (0.33 \cdot 0.495) + (1 \cdot 0.2544) + (3 \cdot 0.1525) + (5 \cdot 0.0637) + (7 \cdot 0.0344) = 1.436373$
- $V_3 = (0.2 \cdot 0.495) + (0.33 \cdot 0.2544) + (1 \cdot 0.1525) + (5 \cdot 0.0637) + (5 \cdot 0.0344) = 0.826961$
- $V_4 = (0.14 \cdot 0.495) + (0.20 \cdot 0.2544) + (0.20 \cdot 0.1525) + (1 \cdot 0.0637) + (3 \cdot 0.0344) = 0.319098$
- $V_5 = (0.11 \cdot 0.495) + (0.14 \cdot 0.2544) + (0.2 \cdot 0.1525) + (0.33 \cdot 0.0637) + (1 \cdot 0.0344) = 0.177506$

The weighted sum vector provides us with a measure of the consistency of the eigenvector for each criterion. If all the values obtained were equal, it would mean that the matrix is well constructed and the weights are correctly distributed. In this case there is a discrepancy between the values, therefore, it is necessary to calculate the Consistency Index (CI) and the Consistency Ratio (CR) to verify the quality of the pairwise comparison matrix.
In order to determine these two indices, first we need to calculate the value of λ_{max}, which represents the largest eigenvalue of the pairwise comparison matrix.
To determine the value of λ_{max}, it is necessary to relate the relative weights with the weighted sum vector V and average the values obtained:

$$\lambda_{\max} = \frac{\frac{2.776431}{0.495} + \frac{1.436373}{0.2544} + \frac{0.826961}{0.1525} + \frac{0.319098}{0.0637} + \frac{0.177506}{0.0344}}{5} = 5.368519$$

To check the consistency, we calculate the Consistency Index (CI) and the Consistency Ratio (CR):

$$CI = \frac{5.368519 - 5}{5 - 1} = 0.09213,$$

$$CR = \frac{0.09213}{1.11} = 0.083.$$

The CR value is less than 0.10% so it can be seen that the evaluations taken during the AHP process are valid.
To integrate the AHP weights with the functional variability we apply the FRAM model:

Table 7
FRAM Impact

Criteria	Critical function	Variability	Initial weight AHP	Impact FRAM	Updated weight
Environmental risk	Supplier Management	Moderate	0.495	0.01	0.505
Geopolitical risk	Transport Monitoring	High	0.2544	0.03	0.2844
Demand risk	Demand Forecasting	High	0.1525	0.03	0.1825
Logistics risk	Stability Monitoring	Moderate	0.0637	0.01	0.0737
Supply risk	Regulatory Adaptation	Low	0.0344	0	0.0344

and calculate the updated weights by adding the impact of the variability to the initial weight of each criterion:

- Environmental risk: 0.495 + 0.01 = 0.505;
- Geopolitical risk: 0.2544 + 0.03 = 0.2844;
- Demand risk: 0.1525 + 0.03 = 0.1825;
- Logistics risk; 0.0637 + 0.01 = 0.0737;
- Supply risk; 0.0344 + 0.00 = 0.0344.

We normalize the updated weights:

Table 8
Normalised Weights

Criteria	**Updated weight**	**Normalised weight**
Environmental risk	0.505	0.505/1.08 = 0.47
Geopolitical risk	0.2844	0.2844/1.08 = 0.26
Demand risk	0.1825	0.1825/1.08 = 0.17
Logistics risk	0.0737	0.0737/1.08 = 0.07
Supply risk	0.0344	0.0344/1.08 = 0.03

and determine the percentage contribution to the overall risk, multiply the normalised weights by 100 to obtain the percentage contributions:

Table 9
Contribution to risk

Criteria	Normalised weight	Contribution to risk(%)
Environmental risk	0,47	47,00%
Geopolitical risk	0,26	26,00%
Demand risk	0,17	17,00%
Logistics risk	0,07	7,00%
Supply risk	0,03	3,00%

From the calculations, it is clear that environmental risk (47.00%) remains the dominant factor. However, logistics (7.00%) and demand (17.00%) risks have increased their impact thanks to the integration of functional variability (FRAM). The integrated FRAM/AHP approach highlights how functions with high variability (for example, transport monitoring) can amplify the overall risk, even if they initially had lower weights in the AHP.

5. Discussions and Conclusions

The hybrid FRAM-AHP model demonstrates how combining qualitative and quantitative methods offers deeper insights into supply chain risk management. The Analytic Hierarchy Process (AHP) was first used to categorise risks into five areas: supply, logistics, demand, geopolitical, and environmental. Environmental risk initially emerged as the most significant (49.50%), followed by geopolitical risk (25.44%). However, these weights did not account for operational complexity and functional variability—key factors in determining the actual dynamics of risk propagation. To address this gap, the model FRAM was applied, enabling an in-depth assessment of how system functions interact and vary under different conditions. For example, in the logistics category, transport monitoring showed high variability due to factors like weather and infrastructure issues. Likewise, demand forecasting proved highly unpredictable, amplifying the potential for disruptions. In contrast, environmental risk, while high in impact, showed lower variability, indicating a more stable influence. After integrating FRAM insights, the AHP weights were adjusted to reflect functional variability. Logistics and demand risks rose slightly to 7% and 17%, respectively, while environmental risk remained dominant at 47%. Geopolitical and supply risks also saw modest increases. These results highlight the value of an integrated approach, where the FRAM-AHP model not only sharpens risk prioritisation but also uncovers the dynamic nature of risk propagation. This enables organisations to better allocate resources, focusing on stable yet high-impact risks and addressing operational uncertainties in logistics and demand forecasting.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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