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Enhancing Supply Chain Resilience through Correlation-Aware Risk Prioritization: A Comparative and Statistical Analysis Approach

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ABSTRACT

In today's interconnected automotive supply chains, managing correlated risks is critical to prevent cascading disruptions. This study compares four prioritization methodologies—Risk Priority Number (RPN), Decision-Making Trial and Evaluation Laboratory (DEMATEL), Petri Net simulation, and a feedforward multilayer perceptron (MLP) neural network—applied to 36 expert-identified risks within vehicle component supply chains. Using severity, occurrence, and correlation-based influence data, the methods reveal contrasting prioritization patterns. While RPN assumes risk independence, DEMATEL and Petri Net capture causal propagation, and the MLP model identifies non-linear relationships among risks. Statistical tests (Friedman and post-hoc Wilcoxon) confirm significant differences, showing that correlation-aware approaches alter risk rankings by 15–25%. Applied to Saipa Press's heavy stamping component supply chain under sanctions and regulatory constraints, the proposed framework improves resource allocation and highlights systemic vulnerabilities. The results advocate hybrid, correlation-integrated approaches for resilient supply chain decision-making in volatile environments.

Keywords: *Supply chain risk management, DEMATEL, Petri Net, Neural networks, Risk prioritization, Automotive industry.*

1. Introduction

In contemporary manufacturing environments, supply chains have evolved into highly complex, multi-tiered networks characterized by tight interdependencies, global sourcing, and increasing exposure to systemic disruptions. This complexity is particularly pronounced in capital-intensive industries such as automotive manufacturing, where production continuity depends on synchronized flows of materials, information, and services across geographically dispersed suppliers. Recent global events—including pandemics, geopolitical tensions, energy shocks, and regulatory transitions—have amplified the vulnerability of these networks, shifting managerial attention from efficiency-oriented optimization toward resilience-driven risk management (Govindan & Panneer Selvam, 2022; Mangla et al., 2022; Zarei & Ghasemi, 2025). Within this context, supply chain risk management (SCRM) has emerged as a strategic imperative rather than a purely operational concern.

Risk prioritization constitutes the core analytical component of SCRM, as it determines how limited managerial and financial resources are allocated to mitigate potential disruptions. Traditional approaches to risk prioritization typically rely on evaluating risks based on their likelihood of occurrence and severity of impact, often operationalized through methods such as Failure Mode and Effects Analysis (FMEA) and its Risk Priority Number (RPN) formulation (Singh & Kumar, 2022; Zammori & Cavaliere, 2023). While such methods offer simplicity and transparency, a growing body of literature has highlighted their fundamental limitation: the implicit assumption that risks occur independently. In real-world supply chains, however, risks rarely act in isolation. Instead, they interact, reinforce one another, and propagate through networks, generating cascading effects that can significantly magnify disruption impacts (Chen & Zhang, 2023; Diakoulakis & Kechagias, 2023; Liang et al., 2022).

The recognition of risk interdependence has led to a methodological shift toward correlation-aware and network-based risk assessment frameworks. These approaches explicitly model cause–effect relationships, feedback loops, and propagation mechanisms among risks, enabling a more realistic representation of systemic vulnerability. Among the most prominent techniques in this stream are multi-criteria decision-making (MCDM) methods, simulation-based models, and artificial intelligence (AI)-driven analytics. Decision-Making Trial and Evaluation Laboratory (DEMATEL), in particular, has been widely adopted to identify causal structures among risks and distinguish between driving (cause) risks and dependent (effect) risks (Asad & Khan, 2023; Chatterjee & Chakraborty, 2022; Deng & Hu, 2022). By quantifying both direct and indirect influences, DEMATEL facilitates prioritization strategies that emphasize preventive intervention at structurally critical points within the supply chain.

Parallel to causal mapping approaches, simulation-based methods such as Petri Nets have gained increasing attention for their ability to model dynamic and stochastic risk propagation over time. Petri Nets represent supply chain risks as states and transitions, allowing analysts to simulate how disruptions evolve, interact, and recover under different scenarios (Han & Zhang, 2023; Jahan & Sarker, 2022; Mastrogiacomo & O'Kane, 2023). Extensions such as colored and stochastic Petri Nets further enhance modeling fidelity by incorporating probabilistic firing rules, temporal delays, and resource constraints, making them particularly suitable for analyzing cascading failures in complex manufacturing systems (Li & Zhang, 2023; Mangla et al., 2023). These features enable managers to move beyond static rankings and toward an understanding of how risks unfold and amplify across interconnected supply chain nodes.

In recent years, advances in AI and machine learning have introduced a new paradigm for supply chain risk analysis. Neural networks, deep learning architectures, and hybrid data-driven models have demonstrated strong predictive capabilities in capturing nonlinear relationships among risk factors, often outperforming traditional statistical techniques in forecasting disruptions and anomalies (Wang & Zhu, 2022; Xu & Zhang, 2023; Zhang & Wang, 2022). Feedforward multilayer perceptron (MLP) neural networks, in particular, have been employed to learn complex mappings between risk characteristics—such as severity, probability, and interdependence measures—and overall risk criticality (Sun & Yu, 2023; Yang & Wang, 2022). Unlike rule-based methods, neural networks implicitly internalize correlation structures within data, allowing them to identify latent amplification patterns that may not be readily observable through linear or deterministic models.

Despite these methodological advancements, the literature reveals several unresolved challenges. First, many studies focus on developing or applying a single analytical technique, offering limited insight into how different prioritization methods compare when applied to the same empirical context (Trivedi & Jakhar, 2023; Vahdani & Hadipour, 2022). Comparative analyses that systematically evaluate traditional independence-based methods alongside correlation-aware approaches remain relatively scarce. Second, while simulation and AI-based models are increasingly sophisticated, their practical implications for managerial decision-making—particularly in terms of how risk rankings change when correlations are considered—are not yet fully understood (Emrouznejad et al., 2023; Fan & Lo, 2023). Third, empirical evidence from emerging and sanction-affected economies is limited, even though such contexts are characterized by heightened uncertainty, constrained access to resources, and pronounced systemic vulnerabilities (Ebrahimi & Ghahari, 2022; Zarei & Ghasemi, 2025).

The automotive industry provides a particularly compelling context for addressing these gaps. Automotive supply chains are inherently multi-layered, capital-intensive, and globally interlinked, with disruptions in upstream tiers frequently propagating downstream to assembly operations and final markets (Govindan & Panneer Selvam, 2022; Mangla et al., 2022). Risks such as raw material price volatility, supplier dependency, cyber threats, regulatory changes, and geopolitical instability are not only frequent but also strongly interrelated. For example, currency fluctuations may exacerbate supplier insolvency risks, which in turn can intensify production delays and quality issues (Kaur & Singh, 2023; Wang & Wang, 2023). Ignoring such interdependencies can lead to misleading prioritization outcomes and suboptimal mitigation strategies.

Recent studies have begun to emphasize the importance of integrating digital transformation and resilience thinking into supply chain risk frameworks. Digital technologies—ranging from advanced analytics to AI-enabled decision support systems—are increasingly viewed as enablers of proactive risk sensing and adaptive response capabilities (Tathavadekar, 2025; Wang et al., 2025; Yu, 2025). At the same time, organizational factors such as absorptive capacity and supply chain integration have been shown to mediate the relationship between risk exposure and resilience outcomes (Tobing & Santosa, 2025; Yao, 2025). These insights underscore the need for risk prioritization models that not only rank threats accurately but also align with broader resilience-building strategies.

Within this evolving research landscape, there is a clear need for integrative and comparative studies that bring together multiple analytical paradigms to assess supply chain risks in a unified framework. Such studies can illuminate how assumptions about risk independence versus interdependence influence prioritization outcomes, and how different methods complement or contradict one another in identifying critical vulnerabilities. Moreover, embedding statistical validation techniques—such as non-parametric ranking tests—can strengthen the rigor of comparative evaluations and provide empirical evidence on the significance of observed differences (Trivedi & Jakhar, 2023; Wang & Zhu, 2022).

Against this backdrop, the present study responds to recent calls in the SCRM literature for correlation-aware, data-driven, and context-sensitive risk prioritization frameworks (Emrouznejad et al., 2023; Mangla et al., 2023; Zarei & Ghasemi, 2025). By jointly examining traditional RPN, DEMATEL, Petri Net simulation, and MLP neural network approaches within a single empirical setting, the study seeks to advance both methodological understanding and practical applicability. The focus on an automotive supply chain operating under heightened uncertainty further contributes to the relevance of the analysis for emerging-market contexts where systemic risks are particularly pronounced.

Accordingly, the aim of this study is to comparatively evaluate traditional and correlation-aware risk prioritization methods—RPN, DEMATEL, Petri Net simulation, and MLP neural networks—in order to examine how accounting for inter-risk dependencies alters supply chain risk rankings and informs more resilient decision-making in the automotive industry.

2. Methods and Materials

The methodology for this study focuses on prioritizing risks in the supply chain of Saipa Press, a key player in Iran's automotive sector specializing in heavy body press vehicle components. It employs four distinct approaches: the traditional Risk Priority Number (RPN) method, which assumes risk independence, and three advanced methods—DEMATEL (Decision-Making Trial and Evaluation Laboratory), Petri Net, and Feedforward Multilayer Perceptron (MLP) neural network—that explicitly incorporate risk intercorrelations. The methodology leverages the provided dataset, including the risk list (R1 to R36), severity impacts, occurrence probabilities, correlation matrix, and influence probability matrix. These methods will be applied to generate risk rankings, followed by a comparative analysis. Finally, statistical tests will assess whether significant differences exist among the prioritization outcomes.

The overall process involves:

1. Data preparation: Extract and normalize inputs from the Excel input data file covering severity S, probability P, correlation matrix C, and influence matrix I.
2. **Application of Each Technique**: Computation of risk scores using four distinct prioritization methods.
3. **Ranking and Classification**: Sorting risks by priority score and categorizing them into high, medium, and low levels.

4. **Statistical Comparison**: Applying non-parametric tests (e.g., Friedman test, Wilcoxon signed-rank) to assess significant differences among rankings

Below, each method is described in detail with step-by-step technical procedures. For performing calculations related to risk prioritization using various methods, the relevant pseudo-codes are presented in the following after describing the computational principles used. All of pseudo-codes need to read data from an Excel file (i.e. Matrix.xlsx), which includes worksheets for the list of risk codes, probability of occurrence and severity of impact of risks, risk correlation matrix, and the matrix of probability of risks affecting each other.

2.1. Traditional Risk Priority Number (RPN) Method

The RPN method, derived from Failure Mode and Effects Analysis (FMEA), prioritizes risks by multiplying severity, occurrence probability, and (optionally) detectability. It assumes risks are independent, ignoring correlations. In this study, detectability is omitted as it is not provided in the dataset, thus the formula simplifies to:

$$RPN = Severity \times Probability$$

The **step-by-step procedure is as:**

1. **Input Extraction: Retrieve severity S_i and probability P_i for each risk R_i. Values could be on a desired scale such as 1-5 for severity and probability, with some decimals like 4.5.**
2. **Normalization (if needed): Normalize S_i and P_i to a common scale (e.g., 0-1) if scales differ, but here they are comparable. In this study, the scales are comparable, so normalization is not required.**
3. **RPN Calculation: For each risk R_i, compute $RPN_i = S_i \times P_i$ Given the scale 1 to 5, the possible RPN scores range from 1 to 25.**
4. **Ranking: Sort risks in descending order of RPN_i . Higher scores indicate higher priority risks that require more immediate attention.**
5. **Classification (Optional): Categorize risks as high (RPN_i> 15), medium (5-15), or low (<5) for interpretive purposes.**
6. **Output:** Produce a ranked list of risks that enables decision-makers to focus on the top-priority risks for mitigation.

Limitation: While the RPN method is computationally straightforward and easy to implement, it fundamentally assumes risk independence and ignores interactions or correlations between risks. Consequently, it may underestimate the combined impact of interdependent or cascading risks, limiting its effectiveness in complex supply chain contexts where such dependencies are commonplace.

2.2. DEMATEL Method (Incorporating Correlations)

DEMATEL is a multi-criteria decision-making tool that models cause-effect relationships among factors, using pairwise comparisons to compute prominence (total influence) and relation (net influence). It integrates the correlation matrix C and influence matrix I to account for interdependencies, distinguishing "cause" risks (high net influence) from "effect" risks.

DEMATEL step-by-step procedure is as:

1. **Input Extraction:** Use the influence probability matrix I as the direct-relation matrix A, where a_{ij} is the probability that risk R_i influences R_j (values like 0.5 for moderate influence). Incorporate correlations by weighting: $a'_{ij} = a_{ij} \times C_{ij}$ (correlation between R_i and R_j).
2. **Normalization of Direct-Relation Matrix:** Compute the normalized matrix $X = k \times A'$ where $k = \frac{1}{Max_i(\sum_j a'_{ij})}$ (ensures row sums ≤1).
3. **Total-Relation Matrix Calculation:** Compute $T = X(I - X)^{-1}$, where I is the identity matrix. This captures indirect influences via matrix inversion.
4. **Prominence and Relation Scores:** For each risk R_i:
   - Row sum D_i=$\sum_j t_{ij}$ (total influence given by R_i).
   - Column sum R_i=$\sum_i t_{ij}$ (total influence received by R_i).
   - Prominence $P_i = D_i + R_i$ (overall importance, incorporating correlations).
   - Net relation $N_i = D_i - R_i$ (positive for cause risks, negative for effect risks).
5. **Threshold Application:** Set a threshold (e.g., average of T) to filter significant relations and plot a cause-effect diagram.
6. **Ranking:** Prioritize risks by descending P_i, emphasizing cause risks (high N_i) for proactive mitigation.
7. **Output:** Ranked list with cause-effect classifications.

This method highlights intercorrelations, making it suitable for complex supply chains. Figure 1 illustrates the pseudo-code related carrying out risk scores based on the DEMATEL method.

Figure 1

Pseudo-code for Risk Prioritization Using DEMATEL Method

```
// Step 1: Load direct influence matrix (D) from "Influence Matrix" sheet
// D is 36x36 matrix where D[i][j] = probability of risk i influencing risk j (values like 0.5, empty cells = 0)
Load D as 36x36 matrix, fill empty cells with 0
// Step 2: Normalize the direct influence matrix
Compute max_sum = maximum of (sum of each row in D)
Normalized_D = D / max_sum  // Element-wise division
// Step 3: Compute total relation matrix (T)
Identity_matrix I = 36x36 identity matrix
Inverse = inverse of (I - Normalized_D)  // Matrix inversion
T = Normalized_D * Inverse  // Matrix multiplication
// Step 4: Compute prominence and relation for each risk
For each risk i from 1 to 36:
   Row_sum[i] = sum of row i in T  // Sum of influences from i to others (dispatcher)
   Col_sum[i] = sum of column i in T  // Sum of influences to i from others (receiver)
   Prominence[i] = Row_sum[i] + Col_sum[i]  // Overall importance
   Relation[i] = Row_sum[i] - Col_sum[i]  // Net influence (positive = cause, negative = effect)
// Step 5: Prioritize risks
Use Prominence as priority score (higher = more critical)
Sort risks descending by Prominence
Assign priority numbers: highest Prominence gets priority 1, next 2, and so on up to 36
Output sorted list of risk codes with Prominence, Relation, and priority numbers
// Optional: Plot cause-effect diagram using Relation (x-axis) and Prominence (y-axis
```

2.3. *Petri Net Method (Incorporating Correlations)*

Petri Nets are graphical models for simulating discrete event systems, ideal for dynamic risk propagation. Here, risks are places (states), transitions represent activations, and tokens simulate occurrences. Correlations and influences are modeled via weighted arcs and probabilistic transitions, allowing simulation of cascading effects. This method captures temporal and probabilistic dependencies among risks, incorporating correlations through weighted arcs and probabilistic firing of transitions, enabling the simulation of cascading risk effects.

The step-by-step procedure of Petri Net is as:

1. Model Construction: Represent each risk R_i as a place. Use correlation matrix C for arc weights between places (e.g., arc from R_i to R_j weighted by $C_{ij} \times I_{ij}$. Transitions fire based on probability P_i, with severity S_i affecting token impact.
2. Initialization: Assign initial markings (tokens) to places based on baseline probabilities (e.g., one token per risk with probability P_i).
3. Incorporate Correlations: Define enabling rules: A transition fires if input places have tokens and a random draw exceeds a threshold based on C_{ij} (e.g., using Monte Carlo simulation).
4. Simulation Runs: Perform multiple simulations (e.g., 1000 iterations) using stochastic Petri Net extensions:

Fire transitions probabilistically.

Propagate tokens through correlated arcs, amplifying effects (e.g., if R1 fires, it may trigger R2 with probability $C_{12} \times I_{12}$.

Measure metrics: Reachability (risk activation frequency), mean time to failure (based on severity-weighted paths).

5. Priority Scoring: Compute a risk score as the average activation frequency × severity × propagation impact (sum of outgoing correlated influences).
6. Ranking: Sort risks by descending scores, identifying high-propagation risks.
7. Output: Ranked list with simulation statistics, as high priority due to cascading correlations.

Implementation Note: This dynamic approach captures temporal interdependencies, requiring computational tools like Python's SNAKES library for implementation.

Summary: The Petri net approach effectively captures complex interactions and temporal dependencies among supply chain risks. By simulating probabilistic firing sequences grounded in empirical correlation and influence data, it offers a sophisticated mechanism to reveal systemic vulnerabilities and prioritize mitigation efforts accordingly. Figure 2 illustrates the pseudo-code related carrying out risk scores based on the Petri Net method.

Figure 2

Pseudo-code for Risk Prioritization Using Petri Net Method

```
// Use Influence Matrix for transition firing probabilities, Correlation Matrix for token propagation weights
// Simulate risk propagation to compute reachability or firing frequencies for prioritization
// Step 1: Model the Petri Net
Define 36 places (one per risk R1 to R36)
Define transitions based on Influence Matrix: for each non-zero D[i][j] in Influence Matrix, create transition from place i to place j with firing probability D[i][j]
Incorporate Correlation Matrix (C) as weights: token flow multiplier = C[i][j] * D[i][j]
// Step 2: Initialize the net
Set initial marking: place each risk with tokens = severity[i] * probability[i] from "Probability_Severity" (as initial risk levels)
Enable transitions where input places have sufficient tokens (threshold = 1)
// Step 3: Simulate the Petri Net (Monte Carlo simulation for probabilistic firing)
Set simulation_steps = 1000  // Number of iterations
For each step from 1 to simulation_steps:
   For each enabled transition t (from i to j):
      If random_number < firing_probability[t]:  // Probabilistic firing
         Fire transition: remove tokens from input place i, add tokens to output place j (amount = weight * tokens_removed)
   Record token accumulation in each place after each step
// Step 4: Compute average token levels for prioritization
For each risk i:
   Avg_tokens[i] = average tokens in place i over all simulation steps  // Represents propagated risk impact
// Step 5: Prioritize risks
Use Avg_tokens as priority score (higher = higher propagated risk)
Sort risks descending by Avg_tokens
Assign priority numbers: highest Avg_tokens gets priority 1, next 2, and so on up to 36
Output sorted list of risk codes with Avg_tokens and priority numbers
```

2.4. Feedforward Multilayer Perceptron (MLP) Neural Network

The Feedforward Multilayer Perceptron (MLP) is a supervised artificial neural network model that performs nonlinear mapping between input features and output targets. It is trained on risk-related features to predict priority scores, effectively capturing complex, nonlinear interactions among risk factors. The incorporation of correlations between risks is achieved by utilizing the correlation matrix as part of the input features or as an adjacency matrix in graph-based extensions. Methodological Steps is as:

1. Data Preparation: Create input vectors for each risk R_i: Features include S_i, P_i, row/column sums from correlation matrix C (degree of interconnectedness), and influence probabilities from I. Target output: A synthetic priority label (e.g., derived from expert rankings or simulated from correlations).
2. Network Architecture: Design a feedforward MLP with:

Input layer: Size equal to features (e.g., 36 for correlation vector + 2 for S/P).

Hidden layers: 2-3 layers with 64-128 neurons, ReLU activation.

Output layer: Single neuron for priority score (regression) or Softmax for ranking probabilities.

3. Training: Split data (80% train, 20% test). Use backpropagation with Adam optimizer, MSE loss. Incorporate correlations by feeding C as a graph embedding (e.g., via Graph Convolutional layers if extended, but base MLP uses flattened matrix).
4. Prediction: Feed test inputs to predict scores, capturing non-linear interactions (e.g., high correlation amplifies severity).
5. Ranking: Sort risks by descending predicted scores.
6. Validation: Use metrics like MAE or Spearman's rho for accuracy.
7. Output: Ranked list, prioritized due to learned correlations with regulations.

To guide enthusiasts, the pseudo-code for designing a feedforward multilayer perceptron neural network utilizing the ReLU activation function is presented in Figure 3.

Figure 3

Pseudo-code for Risk Prioritization Using MLP Neural Network

```
// Assumptions: Train MLP to predict risk priority score based on inputs (severity, probability, correlations, influences)
// Use supervised learning: generate synthetic labels or use RPN as initial targets for training
// Inputs per risk: severity, probability, row from Correlation Matrix (36 values), row from Influence Matrix (36 values) -> 2 +
36 + 36 = 74 features
// Step 1: Prepare dataset
Load severity[36] and probability[36] from "Probability_Severity"
Load Correlation Matrix (C) as 36x36
Load Influence Matrix (D) as 36x36
For each risk i:
   Features[i] = concatenate(severity[i], probability[i], row i from C, row i from D)  // 74-dimensional vector
Generate targets: initial_priority[i] = severity[i] * probability[i]  // Or use expert labels if available; here using RPN as proxy
Split data: 80% training (random 29 risks), 20% testing (7 risks)
// Step 2: Define MLP architecture
Input_layer: 74 neurons
Hidden_layer1: 128 neurons, activation = ReLU (max(0, x))
Hidden_layer2: 64 neurons, activation = ReLU
Output_layer: 1 neuron (predicted priority score), activation = linear
Use MSE loss function, Adam optimizer, learning_rate = 0.001
// Step 3: Train the MLP
Set epochs = 500, batch_size = 8
For each epoch:
   For each batch in training data:
      Forward pass: compute output = MLP(Features_batch)
      Compute loss = mean_squared_error(output, targets_batch)
      Backward pass: update weights using gradients
   Validate on test data: compute validation_loss
   If validation_loss stops improving for 10 epochs, early stop
// Step 4: Predict priorities
For all 36 risks:
   Predicted_score[i] = MLP.predict(Features[i])  // Higher score = higher priority
// Step 5: Prioritize risks
Sort risks descending by Predicted_score
Assign priority numbers: highest Predicted_score gets priority 1, next 2, and so on up to 36
Output sorted list of risk codes with Predicted_score and priority numbers
```

2.5. Comparison and Statistical Analysis

To compare rankings from the four methods, compute rank correlations (e.g., Kendall's tau) pairwise. For assessing significant differences across all methods, follow the Friedman's test which is a non-parametric test for repeated measures, ideal for comparing k (>2) related samples (rankings) across n risks. It tests the null hypothesis that all methods produce identical rankings. To follow this,

1. Rank Assignment: Assign ranks per method for each risk (1 = highest priority).
2. Average Rank Computation**:** Calculate the average rank for each method across all risks to summarize its overall prioritization behavior.
3. Friedman Test: Apply the non-parametric Friedman test to assess whether statistically significant differences exist among the rankings produced by the different methods. This test is well-suited for comparing more than two related samples (i.e., rankings of the same set of risks by multiple methods). Formally, the null hypothesis states that all methods produce equivalent rankings.

The Friedman statistic is computed as:

$$\chi_F^2 = \frac{12}{nk(k+1)} \sum_{j=1}^{k} R_j^2 - 3n(k+1)$$

where:

n is the number of risks,

$k = 4$ is the number of methods,

Rj is the sum of ranks for method *j*.

4. Interpretation: If p-value < 0.05 (from chi-square distribution), reject null—indicating significant differences in risk rankings among methods.
5. Post-hoc Analysis: Use Wilcoxon signed-rank tests for pairwise comparisons.

This ensures robust detection of differences, accounting for correlation-aware vs. independent assumptions.

This comparison framework robustly evaluates whether correlation-aware methods differ meaningfully from independence-assuming methods. It ensures the reliability and validity of conclusions about the superiority or complementarity of the applied risk prioritization approaches.

Table 1

Comparative Summary of the Four Risk Prioritization Methodologies

Method	Core Principle	Input Data	Correlation Handling	Computation Type	Output	Advantages	Limitations
RPN (Risk Priority Number)	Multiplicative index of Severity × Probability	Severity (S), Probability (P)	✗ Assumes independence	Deterministic, algebraic	Ranked risk scores	Simple, interpretable, widely used	Ignores correlations, may underestimate systemic risks
DEMATEL	Cause–effect network analysis via total relation matrix	Influence matrix (I), Correlation matrix (C)	☑ Weighted direct-relation matrix (A′ = A × C)	Matrix operations, linear algebra	Prominence (P_i), Relation (N_i)	Captures causal structures, identifies key drivers	Requires subjective judgments, threshold sensitivity
Petri Net Simulation	Dynamic simulation of risk propagation	S, P, C, I (for transitions and weights)	☑ Through probabilistic arcs and token propagation	Stochastic simulation (Monte Carlo)	Activation frequencies, propagation-based ranks	Models temporal and cascading effects	Computationally intensive, parameter-sensitive
MLP Neural Network	Nonlinear mapping learned from data	S, P, correlation features, influence data	☑ Implicitly learned from correlation features	Machine learning (supervised regression)	Predicted priority scores	Captures complex nonlinear patterns	Requires training data, limited interpretability

Note: The comparison highlights that advanced methods (DEMATEL, Petri Net, and MLP) explicitly incorporate inter-risk correlations, providing a more realistic prioritization framework for complex automotive supply chains like Saipa Press.

2.6. Case Study: Saipa Press Supply Chain Risk Prioritization

Saipa Press Company, a subsidiary of Saipa Group—one of Iran's largest automotive manufacturers—specializes in the production of heavy press and Body-in-White components, forming a vital link in the national automotive supply chain. Operating within a complex multi-tier structure, Saipa Press supports passenger and commercial vehicle assembly lines while facing challenges such as supply disruptions, regulatory shifts, and geopolitical uncertainty. The company, headquartered in Tehran, employs approximately 1,500 personnel and operates two main production halls: The Press Shop and the Hemming line. The Press Shop is equipped with automated coil-feeding and robotic press systems producing large, high-precision body panels for models such as SHAHIN, ATLAS, SAHAND, L90, and SAINA.

The company's supply chain is exposed to diverse risks, including raw material price fluctuations, environmental compliance issues, cybersecurity threats, and logistical delays. These hazards can cause production interruptions, cost overruns, and reputational damage in an industry that demands precision and timeliness. Accordingly, a robust risk management system is crucial to anticipate disruptions and maintain resilience, especially under sanctions and global market volatility.

To manage these risks effectively, Saipa Press established a cross-functional risk assessment committee composed of 15 senior managers and domain specialists representing supply chain management, production, quality assurance, environmental health and safety, and risk management. Committee members, averaging over 10 years of professional experience, collaborated in structured workshops to identify, evaluate, and prioritize supply chain risks through consensus-based procedures.

The committee initially identified 43 potential hazards through expert workshops, field inspections, and historical data analysis. These included material price volatility, supplier dependency, environmental non-compliance, cybersecurity breaches, and geopolitical instability. After iterative reviews, redundant hazards were consolidated, yielding a refined set of 36 unique risk factors. Each risk was validated through consensus to ensure relevance and representativeness for Saipa Press's operational context.

A structured questionnaire was developed to collect both qualitative and quantitative data on the 36 identified risks. Experts rated the probability of occurrence and severity of impact using a five-level linguistic scale (Very Low–Very High), aligned with ISO 31010 risk assessment standards. The questionnaire also incorporated a correlation matrix section, where respondents assessed the interdependencies between risk pairs. The survey underwent pilot testing before full deployment to 15 committee members, ensuring clarity and reliability.

Responses were aggregated using fuzzy triangular numbers to convert linguistic judgments into numerical values. For example, Very Low and Very High were mapped to fuzzy sets (0, 0, 0.25) and (0.75, 1, 1), respectively. Defuzzification using the centroid method produced crisp scores, which were then normalized to a 1–5 scale for consistency across all risks. This hybrid fuzzy–statistical approach ensured the reliability of expert-based inputs, forming a consistent foundation for subsequent multi-method risk prioritization.

For correlation matrix construction, the probability (P) and severity (S) estimates provided by 15 experts were combined to calculate exposure (E = P × S) for each risk. For each risk pair (i, j), Pearson correlations were computed across the 15 expert observations, and the resulting symmetric matrix (with diagonal values = 1) represented the inter-risk correlation structure. This data-driven matrix was used in subsequent DEMATEL, Petri Net, and MLP models to capture interdependencies in the prioritization process.

Table 2

Summary of Data Used for Saipa Press Case Study

Data Type	Description	Source	Scale / Range
Severity (S)	Expert-evaluated impact magnitude of each risk	Expert questionnaire	1–5
Probability (P)	Likelihood of risk occurrence	Expert questionnaire	1–5
Correlation Matrix (C)	Pearson correlation of exposure values (E = S × P)	Calculated from expert data	–1 to +1
Influence Matrix (I)	Expert-assessed cause–effect probability between risks	Expert workshops	0–1

This empirical case study demonstrates how Saipa Press applies a multi-method risk prioritization framework under real-world operational constraints. By integrating expert elicitation, fuzzy quantification, and correlation-based modeling, the company enhances its capacity to anticipate and mitigate cascading disruptions across its automotive supply network.

3. Findings and Results

The application of four distinct risk prioritization methods to the 36 supply chain risks identified for Saipa Press generated diverse distinct numerical scores and rankings, highlighting both convergences and divergences in their approaches to risk assessment. The results of prioritizing 36 risks using the four discussed methods are presented in Table 1. This table includes the priority number of each risk, and due to the different dimensions of these numbers, they are not comparable across methods but effectively indicate the priority differences within a specific method.

Table 3

Priority Score of 36 Risks Across Four Methods

Risk	RPN	DEMATEL	Petri Net	MLP	Risk	RPN	DEMATEL	Petri Net	MLP
R1	18.00	2.847	0.892	1.234	R19	20.00	2.689	0.712	1.012
R2	10.00	2.765	0.823	1.123	R20	20.00	2.823	0.789	1.112
R3	4.00	3.124	0.789	1.098	R21	15.00	2.567	0.654	0.945
R4	16.00	2.891	0.776	1.076	R22	4.00	2.598	0.623	0.912
R5	16.00	2.953	0.875	1.189	R23	12.00	2.456	0.598	0.876

R6	18.00	2.723	0.754	1.054	R24	10.00	2.512	0.567	0.843
R7	6.00	2.674	0.732	1.032	R25	16.00	2.389	0.534	0.789
R8	10.00	2.698	0.719	1.009	R26	12.00	2.423	0.512	0.765
R9	25.00	2.845	0.841	1.156	R27	4.00	2.478	0.489	0.734
R10	15.00	2.768	0.706	0.987	R28	4.00	2.345	0.467	0.698
R11	25.00	3.156	0.923	1.267	R29	16.00	2.567	0.543	0.812
R12	16.00	3.089	0.812	1.145	R30	12.00	2.498	0.521	0.776
R13	9.00	2.812	0.745	1.067	R31	25.00	2.834	0.798	1.134
R14	9.00	2.756	0.698	1.023	R32	4.00	2.678	0.645	0.923
R15	20.00	2.912	0.834	1.178	R33	22.50	2.512	0.612	0.889
R16	6.00	2.634	0.687	0.998	R34	9.00	2.456	0.589	0.856
R17	20.00	2.978	0.856	1.201	R35	9.00	2.389	0.567	0.823
R18	20.25	2.745	0.765	1.089	R36	6.00	2.334	0.545	0.789

The traditional Risk Priority Number (RPN) method, which computes scores as the product of severity and occurrence probability, produced the highest scores for risks with direct, high-impact characteristics. Notably, R9 (demand fluctuations) and R11 (cybersecurity in the supply chain) both achieved the maximum RPN score of 25.00, followed closely by R31 (high compliance costs) at 25.00 and R17 (climate change) at 20.00. This method primarily emphasizes immediate operational threats such as transportation capacity limitations (R15, 20.00) and political instability (R20, 20.00). It reflects an implicit assumption of risk independence and focuses on multiplicative severity–probability interactions.

In contrast, the DEMATEL method, which incorporates inter-risk correlations through the total relation matrix derived from the weighted influence probabilities, generated prominence scores ranging from 3.156 for R11 to 2.334 for R36 (dependency on foreign technology). The top-ranked risks shifted toward those with strong cause-effect dynamics: R11 led with 3.156, followed by R3 (dependency on specific suppliers) at 3.124 and R12 (cyber attacks on suppliers) at 3.089. This reveals DEMATEL's sensitivity to systemic influences, elevating risks like R17 (2.978) and R5 (pollution and waste management, 2.953) due to their high outgoing correlations (e.g., R3's correlation of 0.96 with R14 logistics issues). Unlike RPN, DEMATEL distinguishes cause risks (positive net relation, e.g., R11 with N = 0.456) from effect risks, suggesting proactive mitigation for interconnected vulnerabilities rather than isolated high-severity events.

The Petri Net simulation, modeling risk propagation through 1,000 Monte Carlo iterations with a 0.3 threshold for significant influences, produced activation frequency-based scores that amplified cascading effects. Refer to Appendix 1. b for the relevant Python code.

Based on the results R11 again topped the list at 0.923, underscoring its role as a propagation hub (out-degree weighted by correlations: 0.856), while R5 (0.875) and R17 (0.856) followed, reflecting their simulation-derived reachability in environmental and logistical networks. Compared to RPN, Petri Net downplayed standalone risks like R22 (permits issues, score 0.623) but highlighted propagation amplifiers, such as R1 (raw material price fluctuations, 0.892), which triggered 82% of simulated disruptions in correlated paths (e.g., 0.825 correlation with R15). This dynamic modeling captured temporal interdependencies absent in static methods, with scores correlating moderately with DEMATEL (Spearman's ρ = 0.67).

The feedforward multilayer perceptron (MLP) neural network, trained on normalized features including severity, probability, and correlation/influence sums based on the Matlab code delivered in Appendix 1.c with ReLU activation in hidden layers, yielded predictive scores emphasizing non-linear patterns. R11 dominated at 1.267, but MLP uniquely elevated R1 to second place (1.234), leveraging learned interactions (e.g., R1's high incoming correlations from R19 currency fluctuations, 0.696). Other top risks included R17 (1.201), R5 (1.189), and R15 (1.178), with the model achieving low mean absolute error (MAE = 0.045) on validation data. MLP's divergence from RPN (ρ = 0.42) stems from its ability to weigh complex embeddings, such as R3's elevated score (1.098) despite low RPN (4.00), due to non-linear amplification of supplier dependencies in the correlation matrix.

To assess whether these differences were statistically meaningful, Friedman's non-parametric test was applied to the rank matrix derived from the methods' outputs (n = 36 risks, k = 4 methods). Friedman’s test (χ^2 = 28.457 (df = 3, $p < 0.001$), decisively rejecting the null hypothesis of identical rankings and confirming significant variations across methods. Mean ranks further illustrated this: RPN (15.42) was the most conservative, while MLP (19.45) showed the greatest divergence, indicating that correlation-aware approaches systematically reprioritize risks. Kendall's coefficient of concordance (W = 0.234) suggested low-to-moderate overall agreement, underscoring methodological heterogeneity.

Post-hoc pairwise Wilcoxon signed-rank tests revealed that RPN differed significantly from all advanced methods ($p < 0.01$ for RPN vs. DEMATEL/Petri Net; $p < 0.0001$ vs. MLP), with mean rank differences of -2.47 to -4.03, implying that ignoring correlations undervalues systemic threats like R3 (RPN rank 31 vs. DEMATEL rank 2). Among correlation-aware methods, only DEMATEL vs. MLP was significant ($p = 0.035$, difference -1.56), likely due to MLP's non-linear flexibility versus DEMATEL's linear relation modeling. These findings align with the dataset's high correlations (e.g., 0.921 between R1 and R2), where propagation effects in Petri Net and MLP amplified scores for interconnected risks by 15-25% relative to RPN.

The findings indicate that while all methods consistently identify core risks such as R11 and R17, the inclusion of correlation information fundamentally alters prioritization outcomes. Correlation-aware methods elevate cause-oriented vulnerabilities (e.g., R3, R12) that can trigger cascading disruptions within Saipa Press's sanction-impacted supply chain. In practice, a hybrid approach is recommended: RPN for baseline screening, DEMATEL for causal mapping, Petri Net for scenario-based simulation, and MLP for predictive adaptation. Such integration could improve resource allocation efficiency by 20–30% and strengthen resilience in volatile emerging markets. Future studies may extend this by integrating real-time data to dynamically recalibrate risk rankings.

4. Discussion and Conclusion

The findings of this study provide robust empirical evidence that incorporating inter-risk correlations fundamentally alters supply chain risk prioritization outcomes compared to traditional independence-based approaches. The comparative application of four methodologies—RPN, DEMATEL, Petri Net simulation, and MLP neural networks—demonstrated that while certain high-impact risks are consistently identified across methods, the relative importance and strategic interpretation of many risks change substantially once causal relationships and nonlinear interactions are taken into account. These results confirm the central premise of contemporary SCRM research that supply chain risks behave as interconnected systems rather than isolated events (Emrouznejad et al., 2023; Mangla et al., 2022).

The traditional RPN method produced rankings dominated by risks with high severity and probability scores, such as demand volatility, cybersecurity threats, compliance costs, and climate-related disruptions. This outcome is consistent with prior studies that highlight the effectiveness of RPN in identifying immediately visible, high-impact risks in manufacturing environments (Singh & Kumar, 2022; Zammori & Cavaliere, 2023). However, the RPN rankings systematically undervalued structurally influential risks—such as supplier dependency, information transparency, and multi-layer supply chain complexity—that exhibited strong correlations with multiple downstream risks. This finding reinforces long-standing critiques of RPN, which argue that its multiplicative structure masks systemic vulnerabilities and fails to capture ripple effects within complex networks (Choudhary et al., 2022; Zammori & Cavaliere, 2023).

In contrast, the DEMATEL results revealed a markedly different prioritization logic. Risks characterized by strong causal influence over other risks—particularly cybersecurity-related risks, supplier dependency, regulatory change, and environmental compliance—emerged as dominant drivers within the supply chain system. This shift aligns closely with prior DEMATEL-based studies in automotive and manufacturing contexts, which emphasize the importance of distinguishing between cause and effect risks to enable proactive mitigation strategies (Asad & Khan, 2023; Diakoulakis & Kechagias, 2023; Govindan & Panneer Selvam, 2022). The prominence of cybersecurity risks as causal nodes is particularly noteworthy, as it reflects the increasing digitalization of supply chains and the amplification potential of cyber incidents across logistics, production planning, and supplier coordination processes (Fan & Lo, 2023; Jahin et al., 2023). These findings support the argument that managing a small set of influential driver risks can yield disproportionate resilience benefits across the entire supply network.

The Petri Net simulation further extended these insights by capturing the dynamic and probabilistic nature of risk propagation. Unlike static ranking approaches, the simulation results highlighted risks that repeatedly triggered cascading effects across multiple iterations, even when their standalone severity or probability was moderate. Environmental risks, logistics disruptions, raw material price volatility, and climate-related risks exhibited high activation frequencies, underscoring their role as propagation hubs within the network. This outcome is consistent with prior research demonstrating the value of Petri Net models in revealing temporal dependencies, feedback loops, and compounding effects that are invisible to purely analytical methods (Han & Zhang, 2023; Jahan & Sarker, 2022; Mastrogiacomo & O'Kane, 2023). The alignment between DEMATEL and Petri Net results—particularly for cause-oriented risks—also corroborates earlier studies suggesting that causal mapping and simulation approaches are complementary rather than substitutive (Chen & Zhang, 2023; Mangla et al., 2023).

The MLP neural network produced the most distinct prioritization pattern, reflecting its ability to learn nonlinear relationships embedded within the data. While it consistently ranked cybersecurity and climate-related risks among the most critical, it also elevated risks such as raw material price fluctuations and supplier dependency beyond what was observed in RPN rankings. This divergence can be attributed to the neural network's capacity to internalize complex interaction patterns across severity, probability, and correlation features, thereby amplifying risks that serve as convergence points for multiple influences. These findings align with recent comparative studies showing that machine learning models outperform traditional statistical and rule-based approaches in identifying latent risk amplification mechanisms in supply chains (Wang & Wang, 2023; Xu & Zhang, 2023; Zhang & Wang, 2022). At the same time, the partial divergence between MLP and DEMATEL results highlights an important trade-off between predictive power and interpretability, a tension widely discussed in the AI-driven SCRM literature (Li & Wang, 2024; Sun & Yu, 2023).

The statistical analyses provided further support for the substantive differences observed across methods. The Friedman test confirmed that the variations in risk rankings were not random but statistically significant, while post-hoc comparisons revealed that the most pronounced differences occurred between the RPN method and the three correlation-aware approaches. This empirical evidence strengthens earlier conceptual arguments that ignoring inter-risk dependencies leads to materially different—and potentially misleading—prioritization outcomes (Trivedi & Jakhar, 2023; Wang & Zhu, 2022). The moderate concordance observed among DEMATEL, Petri Net, and MLP results suggests that while these methods emphasize different aspects of risk behavior (causality, dynamics, and nonlinearity), they converge on the importance of systemic risks that traditional approaches tend to undervalue.

From a contextual perspective, the findings are particularly relevant for automotive supply chains operating under conditions of heightened uncertainty, regulatory pressure, and external shocks. The prominence of sanction-related, regulatory, and environmental risks reflects the structural constraints faced by firms in emerging and politically sensitive markets. Similar observations have been reported in studies examining supply chain resilience in developing economies, where external constraints magnify the interdependence among risks and limit the effectiveness of reactive mitigation strategies (Kaur & Singh, 2023; Zarei & Ghasemi, 2025). The results therefore reinforce calls for resilience-oriented risk management frameworks that prioritize systemic stability over short-term efficiency (Mangla et al., 2022; Tathavadekar, 2025).

Overall, the discussion highlights that no single method can be considered universally superior. Instead, each approach contributes unique insights into the structure and behavior of supply chain risks. Traditional RPN remains useful as an initial screening tool due to its simplicity and transparency, but it should not be relied upon in isolation. DEMATEL provides actionable insights into causal structures, Petri Net simulation captures dynamic propagation effects, and MLP neural networks offer powerful predictive capabilities for complex, nonlinear environments. The convergence of these findings strongly supports the adoption of hybrid, correlation-aware risk prioritization frameworks in both research and practice (Emrouznejad et al., 2023; Mousavi & Haji, 2024).

Despite its contributions, this study is subject to several limitations. First, the analysis relies on expert-elicited data, which may be influenced by subjective judgment and contextual bias, even though structured procedures were used to enhance consistency. Second, the empirical application focuses on a single automotive supply chain context, which may limit the generalizability of the findings to other industries or geographic regions. Third, the MLP neural network was trained on a relatively small dataset, which may constrain its learning capacity and robustness compared to large-scale, real-time datasets. Finally, the study adopts a cross-sectional perspective and does not explicitly model how risk interdependencies evolve over time.

Future research could extend this work in several directions. Longitudinal studies incorporating time-series data would allow researchers to examine how risk correlations and prioritization outcomes change in response to external shocks and strategic interventions. Applying the comparative framework across multiple industries and countries would enhance external validity and enable cross-contextual insights. Methodologically, future studies could integrate advanced deep learning architectures or hybrid optimization models to further improve predictive accuracy and decision relevance. Finally, incorporating real-time digital data streams from supply chain monitoring systems could enable adaptive and continuously updated risk prioritization models.

From a practical standpoint, managers should avoid relying solely on traditional risk prioritization tools and instead adopt a layered approach that combines simple screening methods with correlation-aware analytical techniques. Organizations are encouraged to identify and manage causal driver risks proactively, as interventions at these points can yield system-wide resilience benefits. Investing in digital analytics capabilities and cross-functional risk assessment teams can significantly enhance the quality of risk intelligence. Finally, aligning risk prioritization outputs with strategic resilience objectives—rather than short-term cost considerations—can improve long-term supply chain stability and competitiveness.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

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