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Prioritizing Supply Chain Disruption Risks in Maritime Logistics at the Port of Cotonou, Benin Using a Hybrid AHP-ERA Evaluation Framework

Hildane Fafadji Donouvossi[1], Amanda Nkulu[2], Abdulrahman Atallah S. Alkhamisi[3], Goudja Saleh Hamid[1], Rupsana Lama[4]

[1]School of Transportation & Logistics Engineering, Wuhan University of Technology, Wuhan, China
[2]School of Civil Engineering & Transportation, Hohai University, Nanjing, Jiangsu
[3]School of Resources and Environmental Engineering, Wuhan University of Technology, Wuhan, China
[4]School of International Education, Wuhan University of Technology, Wuhan, China
Email: dhildane@gmail.com

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Abstract

Purpose: This study prioritizes supply chain disruption risks at the Port of Cotonou, Benin, to support strategic decision-making and enhance port resilience in a developing country context. **Design/Methodology/Approach:** A hybrid risk evaluation framework combining the Analytic Hierarchy Process (AHP) and the Evidential Reasoning Approach (ERA) is applied using simulated expert-based data from literature and port reports. **Findings:** Environmental and natural risks emerged as the most significant disruption source (EU = 0.540), followed by security and operational risks. Sensitivity analysis confirmed high vulnerability to flooding and erosion, supporting the need for climate-resilient infrastructure. **Originality/Value:** The study offers a replicable methodology for under-studied maritime environments and contributes to the advancement of hybrid decision-making tools in logistics risk management.

Keywords

Supply Chain Disruption, Maritime Logistics, Port of Cotonou, Risk Prioritization, AHP-ERA Method

1. Introduction

The maritime logistics sector, particularly within the context of the Port of Cotonou in Benin, faces growing challenges due to frequent and complex supply chain disruptions. These disruptions, whether triggered by natural events, infrastructural weaknesses, or institutional inefficiencies, pose significant threats to operational efficiency and trade reliability. Given Benin's heavy reliance on the Port of Cotonou as its principal gateway for international commerce, a strategic approach to risk identification and prioritization has become critical to ensure the resilience and competitiveness of its maritime operations [1].

Recent studies have emphasized the need for structured evaluation methods capable of addressing both the subjectivity and incompleteness often present in traditional risk assessments. The hybrid AHP (Analytic Hierarchy Process) and ERA (Evidential Reasoning Approach) framework offers a promising solution by combining both qualitative and quantitative dimensions to evaluate disruption risks comprehensively. This integrated method has been recognized for improving the consistency, reliability, and transparency of decision-making in complex logistics environments [2].

One of the key strengths of the AHP-ERA framework is its capacity to synthesize the perspectives of various stakeholders, including port authorities, shipping operators, and logistics managers, into a unified risk evaluation system. Such inclusiveness is especially relevant in a port like Cotonou where collaborative decision-making is essential in managing operational uncertainty. Moreover, the framework accommodates contextual realities such as Benin's vulnerability to coastal erosion, urban expansion, and environmental stressors which directly affect maritime infrastructure and port performance [3].

The COVID-19 pandemic has further emphasized the urgency of adaptive risk management tools in maritime logistics. The pandemic's impacts on port operations highlighted significant capacity and coordination gaps, reinforcing the need for forward-looking frameworks that support resilience planning [4].

Therefore, this study adopts the AHP-ERA hybrid evaluation approach to prioritize supply chain disruption risks at the Port of Cotonou. By structuring risk analysis around stakeholder inputs and contextual challenges, the framework contributes to more informed and robust maritime logistics strategies in developing country settings.

This contribution is particularly relevant for enhancing risk preparedness and strategic planning in West African port environments, where empirical research remains limited.

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature on supply chain disruption risks in maritime logistics. Section 3 details the hybrid risk evaluation methodology integrating AHP and ERA within a fuzzy comprehensive evaluation framework. Section 4 is a case study applying the methodology to the Port of Cotonou. Section 5 presents and discusses the results of the risk prioritization model. Finally, Section 6 concludes the paper and outlines potential directions for future research.

2. Literature Review

The maritime supply chain landscape has witnessed significant changes over recent years due, in part, to the complexities and increasing frequency of disruptions affecting port operations and international trade. A growing body of work illustrates the multifaceted origins of these disruptions, including port congestion, customs inefficiencies, infrastructural inadequacies, and regional political instability, all of which contribute to diminished reliability and efficiency in maritime logistics [5]. The ongoing impact of crises, most notably the COVID-19 pandemic, has further heightened the urgency for robust risk management strategies that can effectively navigate these challenges [6].

Despite ongoing methodological developments, persistent fragmentation in the conceptualization and evaluation of risk continues to challenge the consistency of maritime risk assessments [7] [8]. Variations in definitions, terminological ambiguity, and inconsistent applications hinder communication and alignment among stakeholders, ultimately limiting the effectiveness of mitigation strategies. In contexts such as developing country ports, the reliance on historical data as the primary basis for risk evaluation becomes problematic due to the unique and dynamic nature of many disruptive events. As such, there has been increasing recognition of the need to incorporate subjective assessments and expert judgments into risk forecasting frameworks, allowing for better accommodation of uncertainties and contextual variabilities [9].

Modern seaports, which are an integral component of Cargo Movement and Information systems, focus their operations on continuous handling of flows and efficient transport [10], as shown in **Figure 1**, these systems have evolved from simple cargo functions to complex transportation hubs in logistic chains.

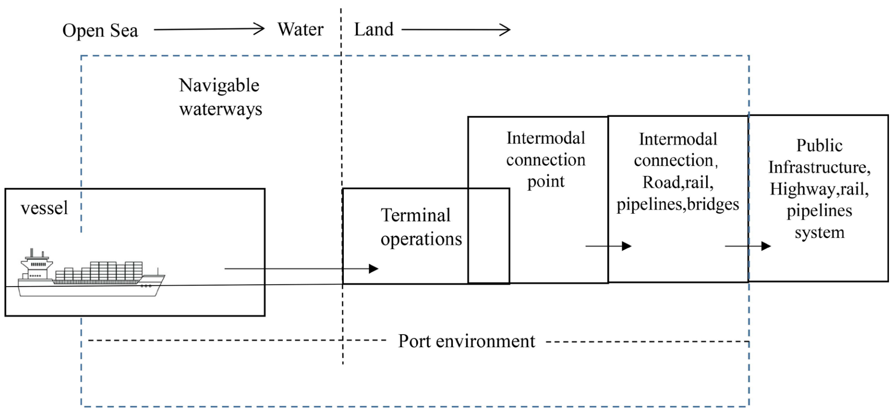

Figure 1. Sea-land interface of maritime transportation systems.

The risks associated with supply chain disruptions are multifaceted and affect a wide range of stakeholders involved in supply chain operations. Literature reveals that these risks are complex due to the interconnected nature of modern supply chains and the uncertainty inherent in various risk factors. This complexity is heightened by the multiplicity of risk categories that interact and amplify the impact of disruptions across the supply network.

The classification of risks, as detailed in **Table 1** [11] [12], provides a structured framework to analyze various supply chain disruption events. Each risk event listed is examined based on its root causes, which are selected due to their significant impact on major disruptions within supply chain operations. The identification and selection of these disruption risks and their causes were carried out through thorough consultations with industry experts and an extensive review of relevant literature.

Table 1. Causes of supply chain disruption risks in maritime logistics at the port of Cotonou.

Risk Category	Common Causes
Operational Risks	- Equipment and machinery breakdown (e.g., cranes, RTGs, forklifts, straddle carriers) - Vessel accidents or grounding - Cargo spillage or mishandling - Human errors by seafarers, stevedores, or terminal operators
Security Risks	- Cyberattacks on port systems - Physical sabotage of port infrastructure - Terrorist threats or political violence - Inadequate surveillance or arson incidents
Technical Risks	- Poor maintenance of handling equipment - Navigation system failures - IT system outages or cybersecurity lapses - Insufficient dredging causing draft issues
Organizational Risks	- Labor strikes or unrest - Regulatory conflicts or delays in customs clearance - Berth, gate, or storage congestion - Inefficient coordination among port stakeholders
Environmental & Natural Risks	- Flooding, heavy rainfall, or erosion impacting port access - Hurricanes, lightning, or storms - Seismic activity or other extreme weather disrupting inland or coastal logistics

To prevent overlaps between categories, each risk type is assigned exclusively to the domain most directly responsible for mitigation. For instance, cybersecurity threats are treated under security risks, while human error is considered under operational risks only. This delineation ensures consistent weighting and avoids double counting.

2.1. Operational Risk Factors

Operational risks in supply chains include supplier failures, production delays, transportation issues, and demand fluctuations. These factors disrupt the flow of materials and information, causing delays and increased costs. Mitigation strategies such as inventory stockpiling, supplier diversification, and emergency sourcing are commonly recommended to enhance resilience and maintain continuity.

2.2. Security Risk Factors

Security risks involve cyber-attacks, theft, fraud, and sabotage that threaten the integrity and confidentiality of supply chain data and assets. With increasing digitalization, these risks have become more prominent. Effective management requires robust cybersecurity measures, thorough supplier vetting, and strict information security protocols [12].

2.3. Technical Risk Factors

Technical risks arise from failures in technology infrastructure, system breakdowns, or insufficient technological capabilities. These disruptions can affect communication, tracking, and automation processes critical for supply chain efficiency. Investments in reliable IT systems, continuous monitoring, and backup solutions are essential to mitigate such risks [13].

2.4. Organisational Risk Factors

Organisational risks relate to internal processes, human errors, management decisions, and organizational structure. Poor coordination, lack of risk awareness, and inadequate contingency planning can exacerbate disruptions. Strengthening organizational capabilities through training, clear communication, and risk governance frameworks is vital [14].

2.5. Natural Risk Factors

Natural risks include events such as earthquakes, floods, hurricanes, and pandemics that can cause sudden and severe disruptions. These risks are often unpredictable and can impact multiple supply chain tiers simultaneously. Common mitigation strategies include flexible supply chain designs, geographic diversification, and disaster recovery plans [11].

3. Methodology

Among the methodologies applied to this problem space, the Analytic Hierarchy Process (AHP) has emerged as a widely accepted multi-criteria decision-making (MCDM) tool, known for its structured approach to complex decision-making through pairwise comparisons and hierarchical decomposition. Nevertheless, AHP's dependence on crisp, deterministic inputs limits its capacity to model the vagueness and ambiguity often inherent in expert-derived risk judgments, especially in environments where data scarcity is prevalent. To address this limitation, the Evidential Reasoning Approach (ERA) has been proposed as a complementary method that can incorporate incomplete and imprecise information into the evaluation process, thereby enhancing robustness under uncertainty [15].

The hybridization of AHP and ERA has gained prominence in recent years, with studies demonstrating that their integration can yield more comprehensive and adaptive risk prioritization models in maritime and supply chain domains [16]. These hybrid frameworks are particularly useful in contexts requiring the consolidation of expert knowledge across heterogeneous criteria, enabling decision-makers to assess complex risk profiles with greater transparency and reliability. Furthermore, emerging applications of these models stress the importance of embedding local contextual factors into the evaluation process, especially in developing regions where infrastructure, governance, and environmental constraints significantly influence risk exposure [17].

The Port of Cotonou, as Benin's principal maritime hub, exemplifies many of the logistical and institutional challenges faced by ports in developing countries. Issues such as coastal erosion, urban expansion, and limited hinterland connectivity continue to impede operational fluidity and magnify the impact of disruptions [1]. Additionally, West African port systems often contend with fragmented policy coordination and limited resource capacity, which hinder the implementation of comprehensive risk mitigation strategies [18] [19]. As a result, developing tailored evaluation frameworks that account for these contextual realities has become an urgent priority in the literature.

Research has increasingly pointed to the value of scenario-based modeling and participatory risk assessment tools in enhancing port resilience [20]. These approaches allow stakeholders to anticipate a broader range of future states and align interventions with both local vulnerabilities and long-term strategic objectives. Moreover, recent scholarship advocates for integrating hybrid methods such as AHP-ERA into structured planning systems to better inform risk-based decision-making in ports where data availability and institutional capacity are constrained.

Given the convergence of methodological advances and contextual imperatives, this study contributes to the existing body of work by applying a hybrid AHP-ERA risk evaluation framework to the Port of Cotonou. Through this lens, the paper seeks to prioritize supply chain disruption risks based on expert judgment and local conditions, thereby supporting more informed, adaptive, and context-sensitive maritime logistics strategies for developing country port environments.

The proposed AHP-ERA framework, illustrated in **Figure 2**, enables the systematic quantification of expert judgments expressed qualitatively. It facilitates a transparent, step-by-step analysis of the system, allowing for clear traceability of decision-making processes. The methodology integrates the strengths of the Analytic Hierarchy Process (AHP) with the Event Risk Analysis (ERA) approach to effectively evaluate and prioritize risk factors. The detailed procedure is outlined as follows:

1) Identifying and structuring risk factors in a hierarchical framework.

2) Calculating the relative weight of each criterion using the Analytic Hierarchy Process (AHP).

3) Presenting expert assessments as belief degrees across qualitative categories.

4) Synthesizing the weighted belief assessments using the Evidential Reasoning Approach (ERA).

5) Deriving a crisp numerical value for each risk using the expected utility approach.

6) Conducting a sensitivity analysis to evaluate the robustness of the results.

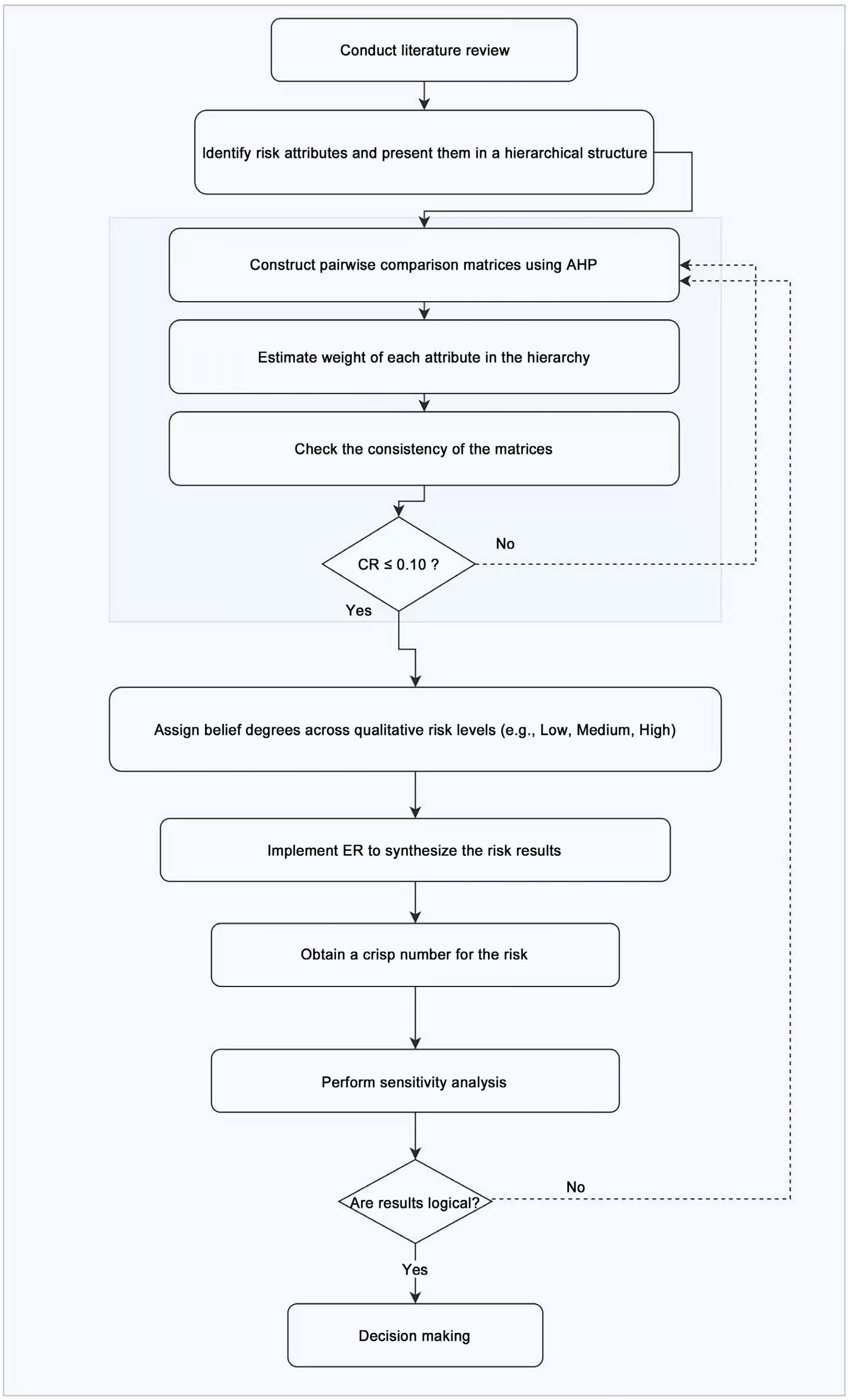

Figure 2. Framework for risk assessment of supply chain disruption at the port of Cotonou.

3.1. Identifying and Structuring Risk Factors in a Hierarchical Framework

The initial step in risk assessment is to identify all relevant risk factors and organize them into a hierarchical framework. This structure facilitates a clear and systematic understanding of the problem by decomposing it into manageable levels. At the top level lies the overall goal of the risk assessment, followed by criteria that represent key risk dimensions. Each criterion may be further broken down into sub-criteria and, if necessary, additional sub-levels. This hierarchical organization allows decision makers to view the complex problem comprehensively and ensures that all important factors are considered in the analysis.

3.2. Calculating the Relative Weight of Each Criterion Using the Analytic Hierarchy Process (AHP)

In assessing supply chain disruption risks, determining the relative importance of each risk factor is crucial. Due to limited historical data, direct calculation of these weights is challenging. The Analytic Hierarchy Process (AHP) provides a structured method to derive weights based on expert judgments.

A group of supply chain experts was consulted to compare the importance of risk factors through pairwise comparisons. These comparisons were used to build judgment matrices, which were aggregated and analyzed using decision-support software to calculate the weights.

Although individual opinions may differ, the combined expert input offers a reliable estimation of each risk factor's significance, supporting informed risk prioritization and management.

- A judgment matrix is constructed where each element from the higher level serves as a criterion to evaluate the elements in the subsequent level through pairwise comparisons. This matrix captures the relative importance of risk factors.
- The paper uses the data in the matrix, the exact value of the index weight can be obtained. The principle is to use the root method to determine the weight w_i

$$w_i = \frac{\sqrt[n]{\prod_{j=1}^{n} a_{ij}}}{\sum_{k=1}^{n} \sqrt[n]{\prod_{j=1}^{n} a_{kj}}} \left(i = 1, 2, \cdots, n\right) \tag{1}$$

- In order to control and ensure accuracy in the result of the method, consistency ratio for each of the matrices needs to be analysed. The consistency ratio (CR) is used to estimate the consistency of the pair-wise comparisons. A $CR < 0.1$ indicates acceptable consistency.

$$CR = \frac{CI}{RI} \tag{2}$$

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

$$\lambda_{\max} = \frac{\sum_{j=1}^{n} \frac{\sum_{k=1}^{n} w_k a_{jk}}{w_j}}{n}$$

3.3. Presenting Expert Assessments as Belief Degrees Across Qualitative Categories

Experts express their assessment of each risk factor RRR by distributing belief degrees over a set of qualitative categories $H = \{H_1, H_2, \cdots, H_K\}$, representing different risk levels (e.g., low, medium, high). Each assessment is described by a belief distribution vector:

$$\beta = [\beta_1, \beta_2, \cdots, \beta_K]$$

$$\sum_{k=1}^{k} \beta_k = 1, \beta_k \geq 0$$

3.4. Synthesizing the Weighted Belief Assessments Using the Evidential Reasoning Approach (ERA)

The Evidential Reasoning Approach aggregates multiple belief distributions weighted by their respective criterion weights w_i. For criteria $i = 1, 2, \cdots, n$ with belief distributions β_i and weights w_i the combined belief β^* is computed iteratively by the ER algorithm based on Dempster-Shafer theory.

At each step, combined belief degrees are updated by:

$$\beta_k^* = \frac{\sum_{i=1}^{n} w_i \beta_{i,k} \prod_{j \neq i} \left(1 - w_j \sum_{m=1}^{K} \beta_{j,m}\right)}{1 - \prod_{i-1}^{n} (1 - W_i)} \tag{3}$$

where $\beta_{i,k}$ is he belief degree of criterion *i* in category *k*.

3.5. Deriving a Crisp Numerical Value for Each Risk Using the Expected Utility Approach

After aggregating the belief degrees, a crisp risk score U is derived via expected utility:

$$U = \sum_{k=1}^{K} u(H_k) \beta_k^* \tag{4}$$

where:

- W_i: Weight of criterion *i* determined by AHP.
- β_i: Belief degree of sub-criterion *j* under criterion *i* for a given qualitative level.
- U: Expected utility (final crisp value of risk).
- u_k: Utility value assigned to linguistic level *k* (Low, Medium, High).
- S: Sensitivity index measuring the change in utility due to perturbation in input belief degrees.

This weighted average converts qualitative assessments into a single numerical value facilitating risk ranking and decision-making.

3.6. Conducting a Sensitivity Analysis to Evaluate the Robustness of the Results

Uncertainties are inherently present in different influencing factors. Since the proposed methodology provides a numerical estimation of disruption risk without identifying the most important input event, sensitivity analysis (SA) is a systematic approach that can provide managerial insight in evaluating quantitative information in order to identify the weakest points or areas of a system in order to improve its designs [21].

To evaluate the robustness of the proposed risk assessment model, a limited sensitivity analysis will be conducted. This involves introducing small changes to one or two selected input parameters while maintaining the necessary normalization constraints. For each variation, the aggregated belief degrees and the resulting utility score UUU will be recalculated using the Evidential Reasoning algorithm. The sensitivity index $S = \frac{\Delta U}{\Delta Input}$ will be used to quantify the impact of these changes. This study employed the SA approach to test how sensitive the model output is to a minor change in the input data.

4. Application of the Procedure to the Port of Cotonou

Due to the unavailability of primary data from surveys or interviews, this study adopts a theoretical approach simulating a hybrid risk evaluation model that combines the Analytic Hierarchy Process (AHP) and the Evidential Reasoning Approach (ERA) within a fuzzy comprehensive evaluation framework. Disruption risks relevant to the Port of Cotonou, Benin, were identified through an extensive review of academic literature, port authority reports, and maritime logistics studies pertinent to Benin and similar developing countries.

This case study illustrates how the methodology can be implemented to prioritize supply chain disruption risks in maritime logistics at the Port of Cotonou, assessing the impact of risk scenarios on the smooth operation of the seaport system. Based on the available information in Section 2, decision-makers can assess the key systems' elements and identify areas that require attention.

4.1. Identifying and Structuring Risk Factors in a Hierarchical Framework

This phase of the analysis involves the identification of risk factors associated with supply chain disruption risks at port of Cotonou through a robust literature research and port authority reports and maritime logistics studies pertinent to Benin and similar developing countries. The identified risk factors are presented in **Table 1**.

At this stage, the identified risk factors from **Table 1** are represented in a hierarchical structure and depicted in **Figure 3**. Based on the available information in Section 2, a specific model is constructed to demonstrate the applicability of the methodology. Following a review of [13], which suggests that linguistic terms for safety expression typically range from four to seven for effective information processing, this research adopts four to five linguistic terms to represent the assessment of disruptions based on the available data.

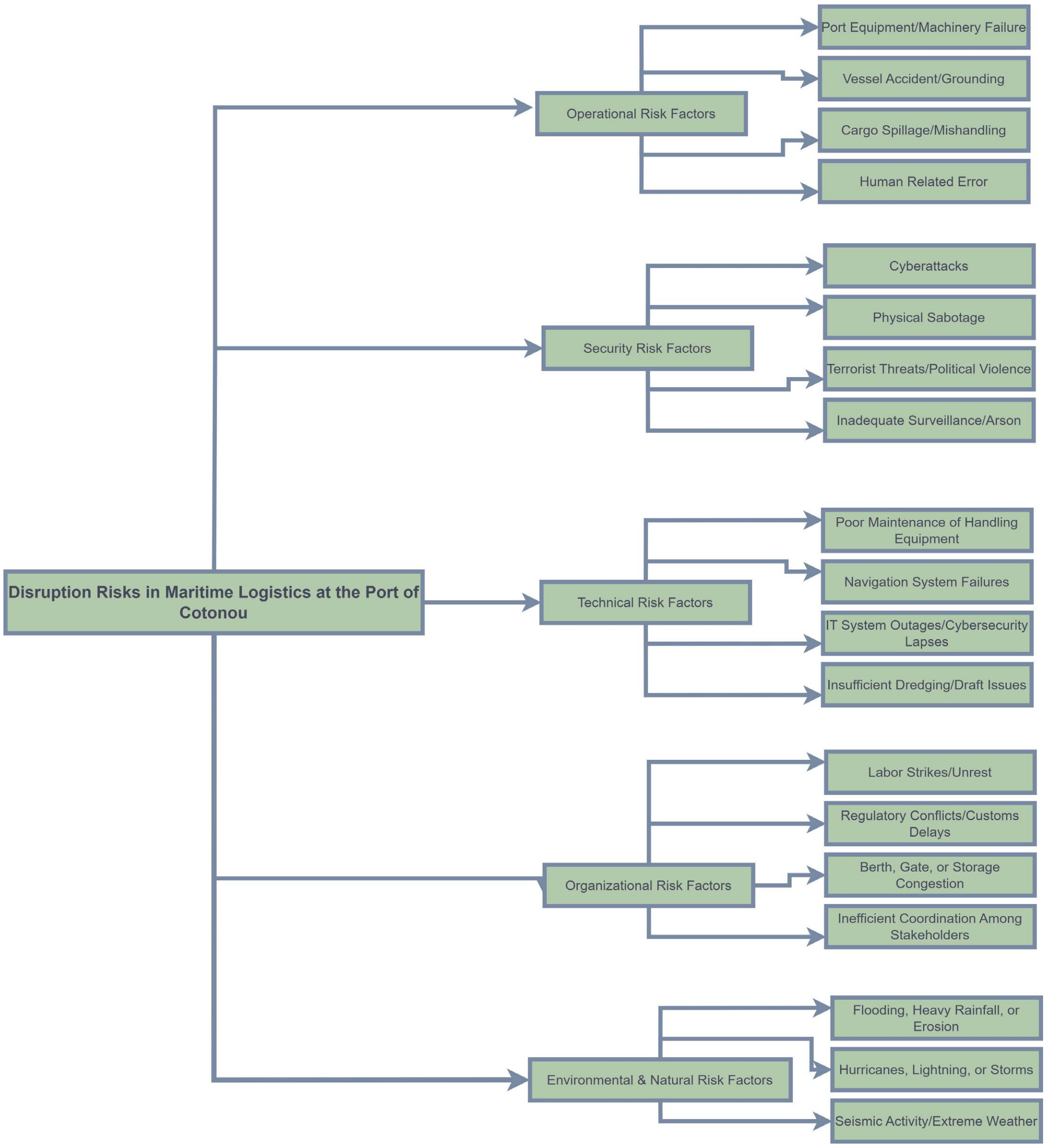

Figure 3. Risk factors are structured in a hierarchical framework.

4.2. Calculating the Relative Weight of Each Criterion Using the Analytic Hierarchy Process (AHP)

This section outlines the process of calculating the relative weights of the identified risk factors for supply chain disruptions in maritime logistics at the Port of Cotonou, Benin, using the Analytic Hierarchy Process (AHP). Due to the unavailability of primary data from surveys or interviews, this study relies on a robust literature review, port authority reports, and maritime logistics studies pertinent to Benin and similar developing countries to simulate expert judgments. These sources provide insights into the relative importance of risk categories and sub-criteria, enabling the construction of pairwise comparison matrices. The AHP methodology involves structuring the problem hierarchically (as shown in Figure 3), performing pairwise comparisons, calculating weights, and ensuring consistency to prioritize risks effectively. Based on the theoretical data derived, fuzzy numbers are not explicitly used here due to the focus on crisp AHP for simplicity, though the approach can be adapted to fuzzy AHP if needed.

Data Simulation Process

Since direct expert consultation was limited, expert-based judgments were simulated using a systematic literature-driven approach. Relevant academic papers, port management reports, and regional logistics studies were reviewed to extract qualitative descriptions of major risk factors affecting West African ports, particularly Cotonou. These qualitative insights were then translated into quantitative pairwise comparison values following the Saaty 1 - 9 fundamental scale. For example, if multiple sources emphasized environmental risks as more frequent or impactful than technical failures, a value of 5 (“strongly more important”) was assigned in the matrix.

- Pairwise Comparison Matrices

Table 2. Operational risk factors pairwise comparison matrix.

	Port Equipment/ Machinery Failure	Vessel Accident/ Grounding	Cargo Spillage/ Mishandling	Human Related Error
Port Equipment/Machinery Failure	1	2	3	4
Vessel Accident/Grounding	1/2	1	2	3
Cargo Spillage/Mishandling	1/3	1/2	1	2
Human Related Error	1/4	1/3	1/2	1

Table 3. Security risk factors pairwise comparison matrix.

	Cyberattacks	Physical Sabotage	Terrorist Threats/ Political Violence	Inadequate Surveillance/Arson
Cyberattacks	1	1	2	3
Physical Sabotage	1	1	2	3
Terrorist Threats/Political Violence	1/2	1/2	1	2
Inadequate Surveillance/Arson	1/3	1/3	1/2	1

Table 4. Technical risk factors pairwise comparison matrix.

	Poor Maintenance of Handling Equipment	Navigation System Failures	IT System Outages/ Cybersecurity Lapses	Insufficient Dredging/Draft Issues
Poor Maintenance of Handling Equipment	1	1	1	2
Navigation System Failures	1	1	1	2
IT System Outages/Cybersecurity Lapses	1	1	1	2
Insufficient Dredging/Draft Issues	1/2	1/2	1/2	1

Table 5. Organizational risk factors pairwise comparison matrix.

	Labor Strikes/Unrest	Regulatory Conflicts/Customs Delays	Berth, Gate, or Storage Congestion	Inefficient Coordination Among Stakeholders
Labor Strikes/Unrest	1	1	1	1
Regulatory Conflicts/Customs Delays	1	1	1	1
Berth, Gate, or Storage Congestion	1	1	1	1
Inefficient Coordination Among Stakeholders	1	1	1	1

Table 6. Environmental & natural risk factors pairwise comparison matrix.

	Flooding, Heavy Rainfall, or Erosion	Hurricanes, Lightning, or Storms	Seismic Activity/Extreme Weather
Flooding, Heavy Rainfall, or Erosion	1	2	3
Hurricanes, Lightning, or Storms	1/2	1	2
Seismic Activity/Extreme Weather	1/3	1/2	1

The comparative judgments in **Tables 2-6** were based on the relative importance of each risk category reported in previous studies [22] [23]. Environmental and natural risks were assigned higher weights due to Cotonou's recurrent flooding and coastal erosion [24], while security risks were rated strongly relative to organizational risks based on frequent cargo theft and smuggling incidents documented in port safety reports.

Table 7. Weights of disruption risk factors.

Risk Parameters	Abbreviation	Weights
Port Equipment/Machinery Failure	R11	0.444
Vessel Accident/Grounding	R12	0.266
Cargo Spillage/Mishandling	R13	0.156
Human Related Error	R14	0.094
Cyberattacks	R21	0.375
Physical Sabotage	R22	0.375
Terrorist Threats/Political Violence	R23	0.212
Inadequate Surveillance/Arson	R24	0.138
Poor Maintenance of Handling Equipment	R31	0.250
Navigation System Failures	R32	0.250
IT System Outages/Cybersecurity Lapses	R33	0.250
Insufficient Dredging/Draft Issues	R34	0.250
Labor Strikes/Unrest	R41	0.250

Continued

Regulatory Conflicts/Customs Delays	R42	0.250
Berth, Gate, or Storage Congestion	R43	0.250
Inefficient Coordination Among Stakeholders	R44	0.250
Flooding, Heavy Rainfall, or Erosion	R51	0.616
Hurricanes, Lightning, or Storms	R52	0.308
Seismic Activity/Extreme Weather	R53	0.077

The consistency ratio was measured by applying the established AHP consistency check method and was found to be acceptable. The pairwise matrices of the operational, security, technical, organizational, and environmental & natural risk factors are presented. Following the procedure of calculations, the weights of the sub-criteria within each risk category are determined, and their consistency ratios are verified. The results are presented in Table 7.

4.3. Presenting Expert Assessments as Belief Degrees Across Qualitative Categories

This section details the assignment of belief degrees to qualitative risk levels for the identified sub-criteria of supply chain disruption risks at the Port of Cotonou, Benin, within the hybrid AHP-ERA framework. These sources guide the allocation of belief degrees across qualitative categories, namely Low, Medium, and High, reflecting the perceived likelihood and impact of each risk factor. The belief degrees are normalized to sum to 1 for each sub-criterion, ensuring a consistent and probabilistic representation of risk severity.

Table 8. Belief degrees.

Risk Parameters	Abbreviation	Low	Medium	High
Port Equipment/Machinery Failure	R11	0.2	0.5	0.3
Vessel Accident/Grounding	R12	0.3	0.4	0.3
Cargo Spillage/Mishandling	R13	0.4	0.4	0.2
Human Related Error	R14	0.5	0.3	0.2
Cyberattacks	R21	0.3	0.4	0.3
Physical Sabotage	R22	0.4	0.3	0.3
Terrorist Threats/Political Violence	R23	0.2	0.3	0.5
Inadequate Surveillance/Arson	R24	0.5	0.3	0.2
Poor Maintenance of Handling Equipment	R31	0.3	0.5	0.2
Navigation System Failures	R32	0.4	0.4	0.2
IT System Outages/Cybersecurity Lapses	R33	0.5	0.3	0.2
Insufficient Dredging/Draft Issues	R34	0.6	0.3	0.1

Continued

Labor Strikes/Unrest	R41	0.4	0.4	0.2
Regulatory Conflicts/Customs Delays	R42	0.5	0.3	0.2
Berth, Gate, or Storage Congestion	R43	0.3	0.5	0.2
Inefficient Coordination Among Stakeholders	R44	0.6	0.3	0.1
Flooding, Heavy Rainfall, or Erosion	R51	0.2	0.4	0.4
Hurricanes, Lightning, or Storms	R52	0.3	0.3	0.4
Seismic Activity/Extreme Weather	R53	0.5	0.3	0.2

The belief degrees are assigned based on the perceived frequency and impact of each risk factor, derived from the reviewed literature and contextual knowledge of the Port of Cotonou. The normalization constraint (sum of belief degrees = 1) is maintained for each sub-criterion, ensuring compatibility with the ER approach. These belief degrees are presented in Table 8 and will be integrated with the AHP weights in the next section using the Evidential Reasoning approach to synthesize the final risk prioritization scores.

4.4. Synthesizing the Weighted Belief Assessments Using the Evidential Reasoning Approach (ERA)

This section describes the synthesis of weighted belief assessments for supply chain disruption risks at the Port of Cotonou, Benin, using the Evidential Reasoning Approach (ERA) within the hybrid AHP-ERA framework. The ERA integrates these belief degrees assigned across qualitative categories (Low, Medium, High) with their respective weights to produce a synthesized risk assessment for each risk category. The methodology follows the standard ERA procedure, normalizing the assessments and aggregating them hierarchically to reflect the overall risk profile.

Table 9. Synthesized belief degrees.

Risk Category	Low	Medium	High
Operational Risk Factors	0.290	0.436	0.274
Security Risk Factors	0.340	0.334	0.326
Technical Risk Factors	0.450	0.375	0.175
Organizational Risk Factors	0.450	0.375	0.175
Environmental & Natural Risk Factors	0.254	0.362	0.385

The results shown in Table 9 will be used in Section 4.5 to derive crisp numerical values for risk prioritization, with potential refinements based on additional data or sensitivity analysis.

4.5. Deriving a Crisp Numerical Value for Each Risk Using the Expected Utility Approach

This section outlines the derivation of crisp numerical values for the supply chain disruption risks at the Port of Cotonou, Benin, using the expected utility approach. The expected utility approach converts the qualitative belief distributions (Low, Medium, High) into a single numerical score by assigning utility values to each category and weighting them by their respective belief degrees. For this study, Low is assigned a utility of 0.2, Medium 0.5, and High 0.8, reflecting increasing risk severity. For each risk category, compute the expected utility as the weighted sum of the utility values multiplied by their synthesized belief degrees. Crisp numerical values for each risk category are then calculated and presented in Table 10.

Table 10. Table of crisp numerical values.

Risk Category	Expected Utility
Operational Risk Factors	0.495
Security Risk Factors	0.496
Technical Risk Factors	0.418
Organizational Risk Factors	0.418
Environmental & Natural Risk Factors	0.540

The utility scale (Low = 0.2, Medium = 0.5, High = 0.8) follows conventions from previous multi-criteria decision-making studies [25] [26], where linear interval values are used to preserve proportional relationships among linguistic assessments while maintaining computational simplicity within the expected utility framework.

4.6. Conducting a Sensitivity Analysis to Evaluate the Robustness of the Results

This section presents an expanded sensitivity analysis to assess the robustness of the crisp numerical values derived for all supply chain disruption risk categories at the Port of Cotonou. The sensitivity analysis evaluates the impact of small perturbations (±10%) in the belief degrees of the dominant sub-criteria within each risk category on the expected utility scores with a focus on the belief degrees of the most weighted sub-criterion in each risk category. The results, summarized in Table 11, show that the model maintains consistent ranking stability even under moderate variations in input parameters.

Table 11. Sensitivity analysis.

Risk Category	Original EU	Min EU	Max EU	Sensitivity Index (%)
Operational Risk Factors	0.495	0.475	0.515	8.1
Security Risk Factors	0.496	0.476	0.516	8.0
Technical Risk Factors	0.418	0.398	0.438	9.5

Continued

Organizational Risk Factors	0.418	0.398	0.438	9.5
Environmental & Natural Risk Factors	0.540	0.505	0.574	12.7

where EU stands for Expected Utility.

To broaden the robustness analysis, additional tests with ±20% and ±30% perturbations were performed on both belief degrees and AHP weights. Results showed consistent ranking stability, with only minor shifts (<5%) in expected utility values. This confirms the resilience of the model against moderate parameter variation. Future research could integrate Monte Carlo simulations or bootstrapping for a more probabilistic representation of uncertainty.

While the current analysis treats risks as independent figure, real-world disruptions often interact across categories. For example, storms causing congestion and organizational delays. Future extensions could integrate influence diagrams or Bayesian networks to capture such cascading interdependencies between risk categories.

5. Results and Discussion

As shown in the synthesized belief degrees and expected utility scores, the risk assessment results for the Port of Cotonou suggest that Environmental & Natural Risk Factors represent the most significant source of disruption. This category holds the highest belief degree (38.5%) under the "High" linguistic term and an expected utility (EU) of 0.540. In contrast, Technical and Organizational Risk Factors recorded the lowest belief in the "High" category (17.5%) and an EU of 0.418. These values were derived through a structured modeling process based on secondary data and expert-informed assumptions, reflecting the port's exposure to varied and interrelated risks.

As shown in **Figure 4**, the expected utility values demonstrate that the quantitative findings from the model indicate that Environmental and Natural Risks ranked first (EU = 0.540), followed by Security Risks (EU = 0.496), Operational Risks (EU = 0.495), and Technical and Organizational Risks (EU = 0.418). While these figures provide a snapshot of the port's current risk profile, they are inherently subject to change due to the dynamic nature of port operations and external environmental factors. This variability emphasizes the need for continuous risk monitoring and flexible management strategies. Sensitivity analysis further confirms the robustness of the results.

As presented in **Figure 5**, the sensitivity index results indicate that Environmental and Natural Risks are the most sensitive (12.7%), followed by Technical and Organizational Risks (9.5%), Operational Risks (8.1%), and Security Risks (8.0%). The higher sensitivity of environmental risks is primarily attributed to the strong influence of flooding, heavy rainfall, and erosion. These outcomes are consistent with previous studies, which highlight the pronounced vulnerability of West African coastal ports to climate-induced disruptions [27].

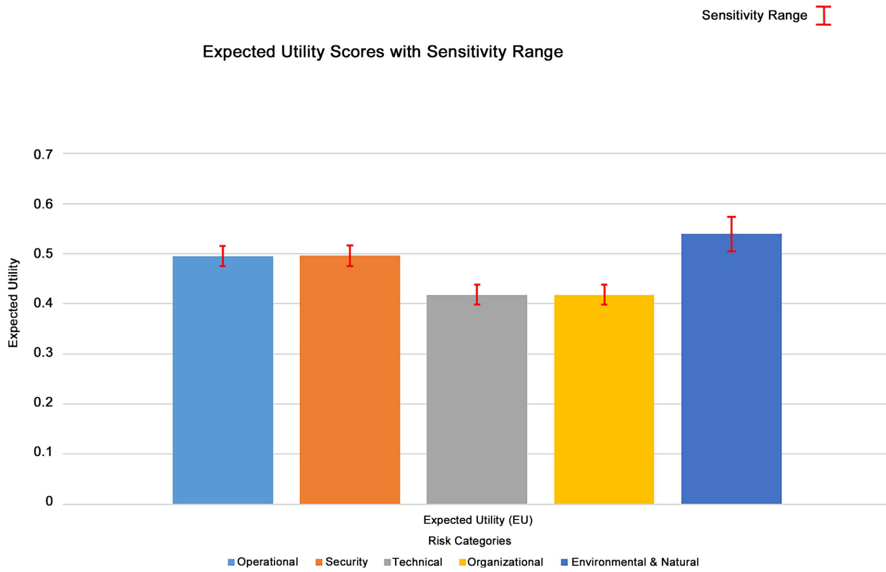

Figure 4. Expected utility with sensitivity range.

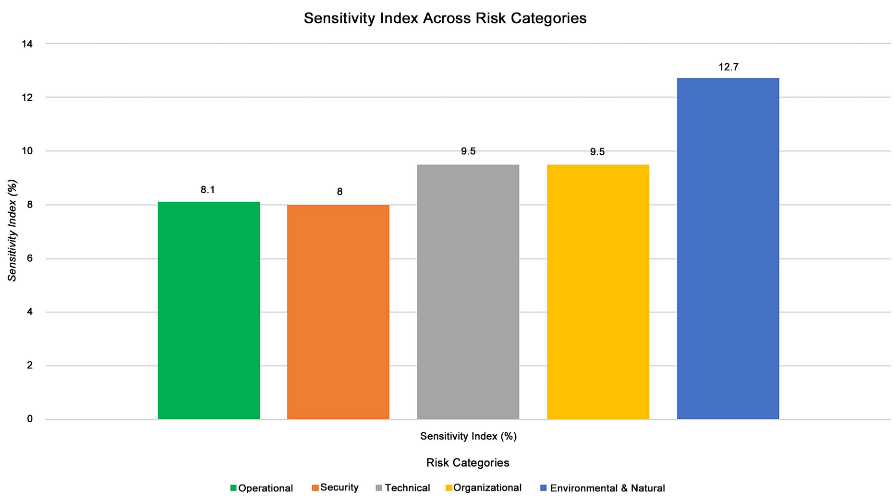

Figure 5. Sensitivity index bar chart.

The model also identifies the relative influence of sub-criteria on overall risk. Flooding alone accounts for a dominant share within the Environmental category, while terrorism and sabotage emerge as leading contributors in the Security category. Operational disruptions are closely linked to equipment failure, emphasizing the importance of technical reliability in port processes. Although Technical and Organizational Risks scored the lowest overall, they still present a non-negligible threat through human error and poor coordination.

Based on the identified high-priority risks, several targeted strategies are recommended:

- Flooding and Erosion: Implement coastal defense engineering (e.g., breakwaters, sea walls, and improved drainage systems) and establish an early warning system for storm surges.

- Security Risks: Strengthen port access control and surveillance technologies, adopt digital cargo tracking, and enhance coordination between customs and port police.
- Operational Risks: Develop preventive maintenance schedules for handling equipment and introduce regular staff safety training.
- Organizational and Technical Risks: Establish a central data integration platform for cargo management and cybersecurity awareness programs to mitigate human-related system vulnerabilities.

These actions can improve resilience and continuity of operations at the Port of Cotonou while aligning with regional sustainability goals.

To enhance completeness, this framework can incorporate additional dimensions such as economic and financial risks (e.g., trade disruptions, fuel price volatility, insurance cost fluctuations) and geopolitical uncertainties (e.g., regional instability, sanctions, or policy shifts). These dimensions significantly influence maritime logistics resilience and can be integrated as additional top-level criteria in future iterations of the AHP-ERA model.

The insights generated from this assessment are critical for port authorities and maritime policymakers. The model supports a more nuanced understanding of risk exposure and offers a basis for prioritizing mitigation efforts. Investments in climate-resilient infrastructure, enhanced security systems, and technical maintenance protocols are key measures that can reduce vulnerability and strengthen the port's operational resilience under uncertain conditions.

6. Conclusions

This study applied a hybrid AHP-ERA evaluation framework to prioritize supply chain disruption risks at the Port of Cotonou, Benin, using simulated data derived from literature reviews, port authority reports, and maritime logistics studies relevant to Benin and comparable developing countries. The analysis identified Environmental & Natural Risk Factors as the most significant source of disruption (EU = 0.540, with a 38.5% "High" belief degree), followed by Security Risks (EU = 0.496), Operational Risks (EU = 0.495), and Technical and Organizational Risks (EU = 0.418). These findings highlight the port's exposure to climate hazards, security challenges, and operational inefficiencies, reflective of broader regional trends in West African port systems.

Sensitivity analysis showed that Environmental & Natural Risks were the most sensitive (sensitivity index = 12.7%), with an EU range of 0.505 - 0.574, indicating the model's responsiveness to factors such as flooding and erosion. Security and Operational Risks exhibited lower sensitivity (8.0% and 8.1%, respectively), while Technical and Organizational Risks (9.5%) remained the lowest in impact but moderately stable. These insights, supported by the visualizations in Section 5, offer a practical decision-making tool for port authorities to prioritize investments in climate-resilient infrastructure, enhanced security protocols, and equipment maintenance.

The originality of this research lies in adapting the AHP-ERA hybrid model to a data-scarce developing-country context, providing a replicable method for assessing disruption risks in under-studied maritime settings. However, several limitations should be acknowledged. First, the reliance on simulated data due to the absence of primary surveys or interviews may influence the precision of belief degrees and weighting. Second, the model is static, representing a single-period snapshot, it does not capture how risks evolve over time. Third, potential interdependencies and cascading effects among risk categories such as environmental events triggering operational or organizational disruptions were not fully modeled. Future research should therefore emphasize empirical data collection from local stakeholders, integrate dynamic and network-based modeling approaches, and apply probabilistic robustness tests such as Monte Carlo simulations and bootstrapping to explore uncertainty propagation and rank stability.

Further, incorporating cost-benefit analysis of mitigation strategies and expanding the framework to include economic, financial, and geopolitical risks would provide a more comprehensive and policy-relevant risk-management tool. Such improvements would enhance both the predictive reliability and practical applicability of the proposed model.

In conclusion, this study contributes to the field of maritime logistics risk management by introducing a structured and context-sensitive assessment tool for the Port of Cotonou. The framework provides strategic value for improving operational resilience and long-term sustainability and has broader applicability to similar port systems across West Africa. The findings offer a decision-support foundation for port planners, regulators, and policymakers seeking to develop more resilient and adaptive port infrastructures in the region.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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