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Analysis of supply chain resilience based on real-world datasets

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Background: Supply chain resilience (SCR) is critical for maintaining business continuity and competitive advantage in a global environment increasingly prone to disruptions like natural hazards and geopolitical tensions. However, a significant problem exists in the lack of standardised, data-driven metrics to compare and monitor vulnerabilities across different transport modes, which hinders effective risk mitigation.

Objectives: This study develops a roadmap for SCR in multimodal transport networks by identifying systemic logistical vulnerabilities. The research focuses on creating dimensionless resilience metrics that can support both real-time operational monitoring and long-term strategic decision-making.

Method: The research employs a quantitative, data-driven strategy. We analysed six real-world datasets – including aviation, maritime, rail, road and an Amazon last-mile delivery case study – through a rigorous pipeline of cleaning, contextual enrichment and indicator calculation.

Results: Findings reveal critical systemic risks: 21% of flights experience disruptions, and rail transport faces a 59% derailment rate. Navigation errors account for 60% of maritime incidents. Furthermore, the case study highlights those orders placed after 17:00 face a 70% delay rate, demonstrating a strong correlation between peak-hour traffic and delivery failure.

Conclusion: The study concludes that understanding the interplay between environmental factors and operational data is essential for proactive resilience.

Contribution: This article contributes a solid foundation for crisis simulation and strategic management. We recommend that logistics managers implement exact actions, such as adjusting delivery schedules based on temporal traffic density and weather forecasts, to meet resilience goals.

Keywords: supply chain resilience; data analysis; real-world datasets; disruption management; supply chain; optimisation; risk mitigation.

Introduction

In today's complex and unpredictable global environment, supply chain resilience (SCR) has become a primary focus for organisations attempting to navigate disruptions ranging from natural disasters and geopolitical tensions to pandemics and cyberattacks. The analysis of SCR is critical for maintaining business continuity and securing a competitive advantage, as it empowers firms to anticipate, absorb and recover from shocks that could otherwise lead to significant operational failure. While the concept of SCR is widely discussed, this study provides industry-specific depth by focusing on multimodal transportation networks – including aviation, maritime, rail and road sectors – and last-mile delivery operations. By utilising six real-world datasets, this research prepares the reader to understand how data-driven insights can be translated into practical resilience strategies across diverse logistical modules.

Resilience in supply chains involves more than just risk management; it requires a proactive approach to identifying vulnerabilities, adapting to changing conditions and rapidly restoring operations after unexpected events. This often includes strategies such as diversifying suppliers, increasing inventory buffers, enhancing collaboration with partners and investing in flexible logistics networks.

In recent years, data analysis has emerged as a powerful tool for strengthening SCR. By leveraging advanced analytics, machine learning and real-time data streams, organisations can gain deeper visibility into their supply chain operations, detect early warning signs of disruption and make more

informed decisions. Data-driven insights enable companies to model potential risks, optimise resource allocation and develop contingency plans tailored to specific scenarios.

The integration of data analysis into supply chain management not only improves responsiveness but also supports continuous improvement. As organisations collect and analyse more data, they can identify patterns, predict future challenges and refine their resilience strategies over time. Ultimately, the combination of robust data analysis and resilient supply chain design empowers businesses to navigate uncertainty and sustain performance in the face of ongoing change.

Literature review

Supply chain resilience has become a central focus in both academic research and industry practice, especially in the wake of global disruptions such as the coronavirus disease 2019 (COVID-19) pandemic. The following detailed review synthesises findings from 20 recent and influential studies, highlighting the evolution, mechanisms, technologies and challenges associated with building resilient supply chains.

Early research established SCR as the ability to anticipate, prepare for, respond to and recover from disruptions, emphasising flexibility, agility, redundancy and collaboration (Belhadi et al. 2021a; Kassa et al. 2023; Wu, Liu & Liang 2024; Zamani et al. 2022). Over time, the concept has expanded to include adaptability and transformation, with a growing emphasis on digitalisation and data-driven decision-making (Dubey et al. 2022; Gupta et al. 2023b; Ivanov 2023; Zamani et al. 2022).

Artificial intelligence (AI) and big data analytics (BDA) are widely recognised as transformative enablers of SCR. Systematic reviews show that AI and BDA support all phases of resilience, that is, readiness, response, recovery and adaptability by enabling real-time risk detection, demand forecasting, scenario simulation and agile decision-making (Beta, Nagaraj & Weerasinghe 2025; Gupta et al. 2023b; Ivanov 2023; Singh, Modgil & Shore 2023; Smyth et al. 2024; Zamani et al. 2022).

For example, Zamani et al. (2022) found that AI and BDA improve SCR by enhancing visibility, responsiveness and adaptability across supply chain phases.

Empirical studies demonstrate that AI-driven transparency, last-mile delivery and personalised solutions for stakeholders are essential for minimising disruption impacts and facilitating agile procurement (Dey et al. 2023; Modgil, Singh & Hannibal 2021b). Artificial intelligence-based multicriteria decision-making frameworks, such as those using fuzzy logic and machine learning, help organisations to identify and implement effective resilience strategies (Beta et al. 2025; Kassa et al. 2023).

Industry 4.0 technologies – including Internet of things (IoT), digital twins and blockchain – further enhance SCR by improving visibility, traceability and information sharing (Gupta et al. 2023b; Ivanov 2023; Riad, Naimi & Okar 2024). Deep learning and explainable AI have been applied to end-to-end resilience management, enabling accurate disruption risk forecasts and real-time mitigation strategies (Mahdi & Sadeghi 2025; Riad et al. 2024).

Digital intelligence technologies also empower sustainable and adaptive supply networks, as highlighted by Dubey et al. (2022). Leadership, organisational culture and employee competencies are essential for successful AI adoption and SCR, particularly in small and medium-sized enterprises (SMEs). Kassa et al. (2023) showed that leadership drives AI adoption, which in turn enhances agility, risk management and sustainable practices.

Human-centric approaches and internal mechanisms are essential for deriving value from digital transformation (Kassa et al. 2023; Shah, Gardas & Narwane 2021; Singh et al. 2024).

In humanitarian supply chains, AI-driven BDA is a significant determinant of agility, resilience, and performance, with organisational practices and information complexity playing key roles (Singh et al. 2023). The unique challenges of humanitarian contexts require tailored frameworks and a practice-based view, as traditional commercial models may not fully apply (Singh et al. 2023; Wu et al. 2024).

Despite the promise of AI and BDA, several challenges persist. These include data quality, integration complexity, cybersecurity, ethical concerns (such as job displacement and privacy) and the need for standardised resilience metrics (Belhadi et al. 2021a; Gupta et al. 2023a; Modgil et al. 2021a; Shah et al. 2021; Smyth et al. 2024). Reviews also highlight a lack of comprehensive frameworks for digital intelligence application and a need for more empirical studies, especially in emerging markets and under-researched sectors (Ahmed et al. 2023; Belhadi et al. 2021b; Dubey et al. 2022; Mahdi & Sadeghi 2025).

Recent literature calls for hybrid AI–human collaboration, greater transparency through explainable models and integration with other digital technologies (Dubey et al. 2022, Mahdi & Sadeghi 2025).

There is also a need for more research on the social and ethical implications of AI in SCR, as well as on the development of robust, scalable and context-specific resilience frameworks (Dubey et al. 2022; Gupta et al. 2023a; Mahdi & Sadeghi 2025; Modgil et al. 2021a; Shah et al. 2021).

Table 1 presents all the themes along with their key insights and corresponding references.

Problem statement

Recent literature recognises AI and BDA as transformative enablers for SCR, supporting phases of readiness, response

TABLE 1: Asummary of key themes and insights with corresponding citations.

Theme	Key insights	Citations
AI and BDA for SCR	Enhance visibility, forecasting, adaptability and decision-making	Zamani et al. (2022); Modgil et al. (2021b); Beta et al. (2025); Singh et al. (2023)
Industry 4.0 and digital technologies	IoT, digital twins, blockchain improve traceability and real-time response	Dey et al. (2023); Gupta et al. (2023b); Smyth et al. (2024)
Organisational and/or Human factors	Leadership, culture and skills drive successful AI adoption	Gupta et al. (2023b); Riad et al. (2024); Ivanov (2023)
Humanitarian supply chains	AI-BDA key for agility and resilience in disaster contexts	Mahdi and Sadeghi (2025); Singh et al. (2024); Kassa et al. (2023)
Barriers and research gaps	Data quality, ethics, integration, lack of frameworks	Shah et al. (2021); Singh et al. (2023); Wu et al. (2024); Belhadi et al. (2021a); Modgil et al. (2021a); Smyth et al. (2024)
Future research directions	Hybrid AI-human, explainable AI, sector-specific studies	Gupta et al. (2023a); Shah et al. (2021); Belhadi et al. (2021b); Ahmed et al. (2023); Dubey et al. (2022); Mahdi and Sadeghi (2025)

AI, artificial intelligence; BDA, big data analytics; SCR, supply chain resilience; IoT, Internet of things.

Note: Please see the full reference list of the article, Skaf, A. & Pallares G., 2026, 'Analysis of supply chain resilience based on real-world datasets', *Journal of Transport and Supply Chain Management* 20(0), a1314. https://doi.org/10.4102/jtscm.v20i0.1314, for more information.

and recovery. However, a significant gap remains in the practical application of these technologies.

Despite the wealth of available data, there is a persistent lack of standardised resilience metrics and a shortage of comprehensive frameworks to guide organisations in their digital transformation. The core problem addressed in this study is the difficulty of quantifying and comparing vulnerabilities across heterogeneous transport modes. Without robust, scalable and context-specific resilience frameworks, organisations struggle to move beyond a reactive stance. This research seeks to solve this by providing a methodological bridge between raw data collection and actionable, real-time risk mitigation.

Purpose of the study

The purpose of this study is to provide a roadmap for the entire research process by establishing a clear view of logistical vulnerabilities. It aims to move beyond theoretical discussion to deliver a robust technical tool, specifically dimensionless metrics, which can be adapted to various supply chain contexts for both long-term strategic planning and real-time operational monitoring.

Research objectives

This study pursues the following specific objectives:

- To identify and categorise systemic logistical vulnerabilities across different transport modes (air, sea, rail, road) using large-scale, real-world datasets.

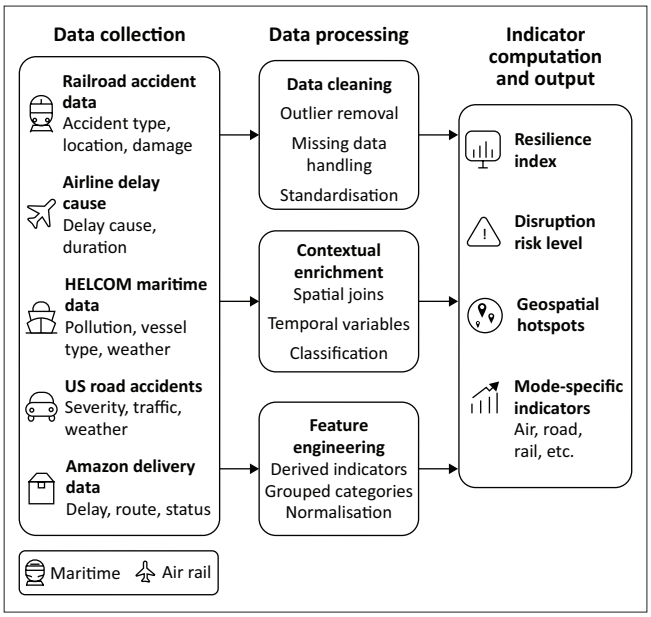


FIGURE 1: An overview of the data collection and processing pipeline used for multimodal supply chain resilience analysis.

- To develop and propose dimensionless metrics and risk indicators (e.g. resilience index, pollution score, disruption score) to standardise the measurement of resilience.
- To analyse the interplay between environmental factors (such as weather and time of day) and delivery performance through a targeted case study on last-mile logistics.

Research strategy and methodology

This section details the systematic investigation and the techniques used to interpret relationships among the study's components. To ensure methodological rigour, this research employs a quantitative, data-driven strategy designed to move beyond a mere listing of variables and provide actionable insights for SCR. The methodology follows a three-step pipeline:

- Data collection: Identifying and selecting publicly available, reliable datasets across multiple transport modes.
- Data treatment: Performing rigorous cleaning and contextual enrichment, including the addition of spatial and temporal variables to improve analytical depth.
- Indicator calculation: Using statistical analysis to interpret relationships among various supply chain components and derive indicators that uncover new information regarding systemic risks.

The process is illustrated in Figure 1.

Research design and strategy

This study is categorised as a quantitative survey of data. The strategy is aimed at uncovering new information regarding logistical vulnerabilities by analysing large-scale, real-world datasets across multimodal transport networks. By processing these datasets through a standardised pipeline, the study ensures that the findings correlate directly with the established research objectives.

Data collection

The first phase involves the selection of six primary real-world datasets that meet criteria for granularity and analytical relevance. As shown in Table 2, the scope includes:

- **Aviation and rail:** Focused on delays, accidents, and economic impacts in the United States.
- **Maritime:** Focused on shipping accidents and pollution in the Baltic Sea.
- **Road and last-mile delivery:** Focused on traffic density, weather impacts, and Amazon delivery schedules.
- **Global logistics:** Focused on supplier reliability and resilience indices.

Data treatment and contextual enrichment

To improve knowledge and interpret complex relationships, each dataset undergoes a rigorous treatment process:

- **Data cleaning:** This includes temporal filtering to remove outdated data and the removal of incomplete rows to ensure data quality.
- **Data validation:** The exclusion of incomplete rows or entries lacking critical spatial-temporal variables, thereby ensuring the integrity of the 'Resilience Index' and other indicators.
- **Contextual enrichment:** To enhance analytical depth, datasets are enriched with spatial variables (geographic zones) and new temporal variables (hour, day and decade). This step is critical for analysing the interplay between environmental factors – such as weather and time of day – and logistical disruptions.

TABLE 2: An overview of transport and logistics datasets with corresponding citations.

Dataset	Parameters	Zone	Citation
Rail incidents			
Railroad Accident and Incident Data (2002–2022)	• Type of accident • Location • damages • victims	Texas, United States	CoreyChristensen (2023)
Flight delays			
USA Airline Delay Cause (2003–2022)	• Weather • Security • airline • Congestion	10 airlines†, United States	Ryanjt (2023)
Maritime accidents			
HELCOM – Shipping Accidents (2003–2023)	• Location • Severity • Pollution • Weather • Vessel type	Baltic Sea	HELCOM (2023)
Road accidents			
US Accidents (2016–2023)	• Severity • Location • Traffic impact • Weather	All states, United States	Moosavi (2023)
Last-mile delivery			
Amazon Delivery Dataset (2022)	• Schedules • Statuses • delays • Zones	Global‡	Suthar (2023)
Logistics KPIs			
Supply Chain Dataset – Natasha0786 (2023)	• Risk scores • Supplier reliability • delivery times	Global‡	Natasha0786 (2023)

Note: Please see the full reference list of the article, Skaf, A. & Pallares G., 2026, 'Analysis of supply chain resilience based on real-world datasets', *Journal of Transport and Supply Chain Management* 20(0), a1314. https://doi.org/10.4102/jtscm.v20i0.1314, for more information.

KPI, key performance indicator.

†, The networks are: Alaska Airlines (AS), Allegiant Air (G4), American Airlines (AA), Delta Air Lines (DL), Frontier Airlines (F9), Hawaiian Airlines (HA), JetBlue Airways (B6), Southwest Airlines (WN), Spirit Airlines (NK), United Airlines (UA); ‡, Global (worldwide, across multiple countries and regions).

Calculation of specific indicators

The final step of the methodology is the development of dimensionless metrics. These indicators, summarised in Table 3, act as a 'robust technical tool' for standardising resilience measurement. Key indicators include the resilience index, pollution score and disruption score, which allow for a rational assessment of findings and support final decision-making in strategic management.

Ethical considerations

This article followed all ethical standards for research without direct contact with human or animal subjects.

Results

Analysis of systemic vulnerabilities across transport modes

In alignment with the first research objective, this study categorises logistical vulnerabilities across four primary transport modes to identify specific points of systemic failure.

Aviation sector vulnerabilities

Analysis of 121 million flights (from 2003 to 2022) reveals that 21% of flights experienced disruptions. The primary vulnerability is temporal, with flight delays accounting for 90% of incidents. The data identify three major systemic bottlenecks: previous aircraft delays (38%), airline operations (31%) and air traffic control (26%). Interestingly, weather (5%) and safety (0.2%) were found to be minor or exceptional factors, suggesting that aviation resilience is primarily dependent on operational and scheduling efficiency rather than environmental shocks.

TABLE 3: Risk indicators by transport mode and supply chain component.

Component or mode	Key indicators
Suppliers	• Resilience index • Route risk level • Disruption score
Air	• Delay rate by cause • Weather • Congestion
Train	• Damage severity • Number of injuries • Hazardous products
Maritime	• Pollution score • Ship profile score • Risk score
Amazon deliveries	• Delivery risk combined with temporal and geographic criteria

Maritime sector risks

The maritime dataset (2003–2023) highlights a significant human-centric vulnerability. Navigation and maneuvering errors account for 60% of all incidents, far outpacing technical failures (6%) or fire/explosions (5%). These disruptions resulted in nearly 1700 tons of pollution in the Baltic Sea, emphasising the high environmental stakes of maritime logistical failures. This identification resulting from maritime incidents underscores a critical failure in meeting the 'Environmental' goals within the ESG (environment, social and governance) framework. As navigation and maneuvering errors account for 60% of these incidents, it is evident that human-centric operational failures are the primary drivers of ecological degradation in this region. Within the context of modern global logistics, adhering to ESG constraints is no longer optional; thus, these findings highlight that maritime SCR must be intrinsically linked to environmental sustainability and corporate responsibility.

To bridge this gap, it is essential to determine the root causes of such pollution through technological innovation. By integrating Industry 4.0 solutions – such as AI-driven real-time navigation monitoring and digital twins – organisations can proactively mitigate the risks associated with human error, thereby ensuring that maritime strategies are not only resilient but also strictly aligned with ESG-mandated environmental protection standards. This transition from reactive recovery to proactive, technology-enhanced monitoring is vital for maintaining the ecological integrity of sensitive maritime zones such as the Baltic Sea while ensuring long-term operational viability.

Rail transport severity

Although rail transport has one of the lowest annual incident rates (approximately 3000), it presents the highest severity in terms of physical and economic impact. Derailments represent 59% of rail incidents, followed by collisions at 18%. These systemic failures lead to an average of 78 deaths per year and an estimated annual economic loss of over $8 billion in the United States alone.

Road infrastructure and traffic density

Road transport experiences the highest frequency of disruptions, with approximately one million incidents annually. The data prove a direct correlation between vulnerability and public domain interaction, particularly during weekday commuting periods where increased traffic density results in an average congestion delay of 5 h per accident.

Validation of proposed resilience metrics

To fulfil the second objective, the findings were synthesised into standardised indicators as detailed in Table 4. These metrics – such as the incident/vehicle number ratio and frequency by incident type – provide the 'robust technical tool' required for cross-modal comparison. For example, the high 20% incident/vehicle ratio in rail versus the 0.36% in road allows managers to prioritise infrastructure investment where the risk per unit is highest.

Geographical mapping of supplier resilience

As observed, each type of transport mode has a variety of incidents with varying prevalence.

In this paragraph, we explore another spatial scale, focusing not on the mode, but on the geographical origin of suppliers. From the dataset (Natasha0786 2023), we extract the resilience index and the study identifies spatial vulnerabilities. As illustrated in Figure 2, the analysis reveals a clear divide: Northern Europe, the US and Australia demonstrate high resilience, whereas regions in Africa, Central America and parts of Asia remain more vulnerable to systemic supply chain shocks.

Case study: Interplay of environmental and temporal factors

The final objective is addressed through the Amazon last-mile delivery case study. The analysis of 43 000 deliveries proves that vulnerabilities are not static but are highly dependent on the interplay of external variables:

- **Temporal factors**: Orders placed after 17:00. face a 70% delay rate, compared to significantly higher reliability in morning slots.
- **Environmental interaction**: A critical correlation exists between weather and traffic quality. In optimal conditions, delay rates fall below 10%, but the combination of heavy rain and traffic jams results in a 90% delay rate.

Conclusion

This study addresses a critical gap in SCR: the lack of standardised, data-driven metrics to compare and monitor vulnerabilities across diverse transport modes. By analysing

TABLE 4: Incidents per year by transport mode.

Mode	Vehicle number	Incidents per year	Incident or vehicle number (%)	Incident type	Frequency (%)
Aviation	214 528	1 352 410	630.00	Delays	90
				Diverted flight	01
				Cancelled flights	09
Maritime	4512	205	4.50	Navigation	59
				Technical failures	06
				Fire or explosion	05
				Pollution	02
				Other	28
Road	274 121 147	996 531	0.36	Traffic accident	100
Train	15 750	3150	20.00	Derailment	59
				Collision	18
				Obstacle on track	03
				Fire or breakage	01
				Other	19

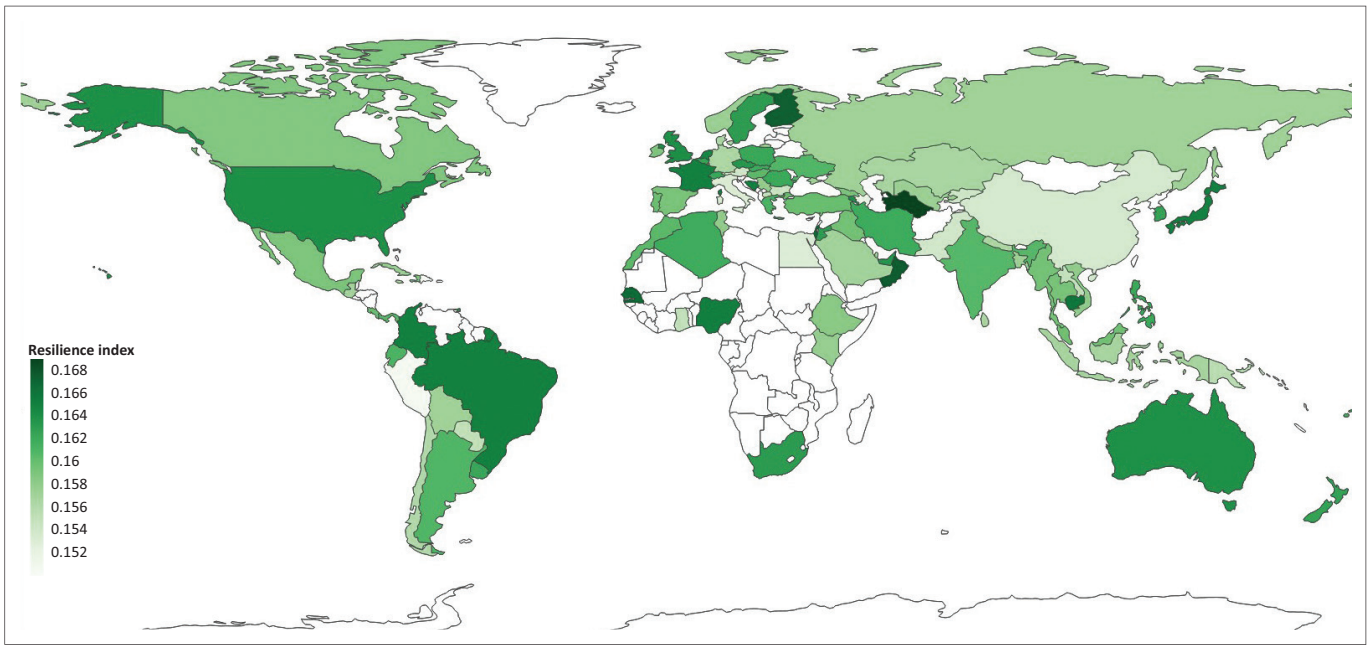


FIGURE 2: Mapping of supplier resilience index by country.

six real-world datasets, we have successfully met our two primary objectives: identifying systemic logistical vulnerabilities and providing a robust technical tool for operational monitoring.

Our findings provide a factual solution to the problem of identifying hidden risks. For instance, the discovery that 21% of flights experience disruptions and that 59% of rail incidents involve derailments highlights where infrastructure-specific resilience must be prioritised. Furthermore, the maritime data reveal that 60% of incidents stem from navigation errors, suggesting that human factors and real-time monitoring remain the most significant points of failure in that sector.

The proposed dimensionless metrics serve as the study's core contribution, offering a scalable method for strategic management and crisis simulation. Instead of merely listing variables, this research demonstrates the interplay between environmental factors and operational success. The Amazon case study, in particular, proves that temporal and weather-related data are predictive of failure, with a 70% delay rate for orders placed after 17:00 and a 90% delay rate during heavy rain and traffic jams.

Recommendations

To address the logistical vulnerabilities identified in this study and fulfil the research purpose of enhancing SCR, the following exact actions are recommended for logistics managers, stakeholders and policymakers:

- **Dynamic last-mile scheduling:** Based on the 70% delay rate identified for evening deliveries, organisations should shift high-priority delivery windows to morning slots and adjust late-afternoon schedules to account for peak-hour traffic density.
- **Proactive weather-based dispatching:** To mitigate the 90% delay risk observed during adverse conditions, firms must integrate real-time weather and traffic quality data into their automated dispatching systems to trigger proactive rerouting or scheduling adjustments.
- **Infrastructure-specific risk prioritisation:** Given that 59% of rail incidents are derailments and 21% of flights face operational disruptions, stakeholders should prioritise infrastructure maintenance for rail networks and focus aviation resilience efforts on optimising aircraft and airline scheduling.
- **Technological intervention in maritime navigation:** As navigation errors account for 60% of maritime accidents, shipping companies should invest in enhanced real-time navigation monitoring and human-factor training to reduce the environmental impact of pollution incidents.
- **Adoption of standardised resilience metrics:** Organisations should implement the dimensionless metrics proposed in this study – specifically the resilience index and disruption score – to standardise the monitoring of vulnerabilities across different transport modes and enable cross-modal risk comparison.

By implementing these actions, organisations can move beyond a reactive stance and achieve the proactive resilience necessary for maintaining business continuity in an unpredictable global environment.

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Competing interests

The authors declare that they have no financial or personal relationships that may have inappropriately influenced them in writing this article.

CRediT authorship contribution

Ali Skaf: Conceptualisation, Data curation, Methodology, Project administration, Resources, Supervision, Validation, Visualisation, Writing – original draft, Writing – review & editing. Gaël Pallares: Conceptualisation, Methodology, Project administration, Supervision, Validation, Writing – original draft, Writing – review & editing. All authors reviewed the article, contributed to the discussion of results, approved the final version for submission and publication, and take responsibility for the integrity of its findings.

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Data availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

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