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An Integrated Resilience Assessment of Aviation Logistics Networks Using Bayesian Networks: A Case Study of Pandemic-Induced Disruptions at a Major Asian Hub

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ABSTRACT

The global aviation logistics network, a critical artery for high-value and time-sensitive supply chains, exhibits significant vulnerability to disruptive shocks. Traditional risk management models, often static and linear, fail to capture the dynamic, non-linear, and cascading nature of such disruptions. This paper proposes a novel methodological framework that integrates the principles of resilience engineering into a Bayesian Network (BN) to quantitatively assess and enhance the resilience of aviation logistics systems. The core innovation lies in structurally embedding the three capacities of resilience—absorptive, adaptive, and restorative—into the BN's topology. A real-world case study of a major Asian air cargo hub (Shanghai Pudong International Airport) during the COVID-19 pandemic is conducted to validate the model. Through predictive, diagnostic, and sensitivity analysis, the model identifies ground staff availability, aircraft redeployment flexibility, and regulatory adaptability as the most critical resilience enablers. The study concludes with strategic, data-driven suggestions for stakeholders to transition from reactive risk mitigation to proactive resilience building, emphasizing investment in human capital, digitalization, and collaborative ecosystem planning.

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1. Introduction

1.1. Background and Motivation: The Fragility and Importance of Global Aviation Logistics

The global aviation logistics network functions as the circulatory system of the modern global economy, indispensable for the rapid movement of high-value, time-sensitive, and critical goods. Its operational paradigm underpins just-in-time manufacturing, the global distribution of perishable commodities, and the explosive growth of international e-commerce. However, this complex, interconnected system—comprising airports, airlines, ground handling agents, freight forwarders, and air traffic control—is profoundly vulnerable to a wide spectrum of disruptions. These range from localized incidents, such as extreme weather events and labor strikes, to global systemic shocks, exemplified by the 2010 Eyjafjallajökull volcanic eruption and the COVID-19 pandemic. The latter event, in particular, served as a stress test, exposing deep-seated systemic fragilities. It triggered an unprecedented collapse in passenger networks (which provide approximately 50% of global air cargo capacity in their bellies) while simultaneously causing a surge in demand for specific goods, such as medical supplies and electronics. This paradox highlighted the critical limitations of conventional risk management approaches and underscored the urgent need for a paradigm shift towards understanding and quantifying system resilience: the ability to anticipate, withstand, adapt to, and recover from disruptive events.

1.2. From Risk to Resilience: A Necessary Paradigm Shift

While traditional probabilistic risk assessment (PRA) models are valuable for understanding specific failure modes, they possess inherent limitations in addressing the complexities of modern aviation logistics. They are often static, linear, and struggle to account for the cascading effects, non-linear interactions, and adaptive behaviors inherent in such complex systems. Resilience engineering offers a complementary yet distinct paradigm. It is not solely concerned with preventing negative events (risk mitigation) but is fundamentally focused on designing and managing systems that can endure, adapt, and maintain core functionality amidst volatility and unexpected shocks. For the purpose of this study, resilience is decomposed into three core, interconnected capacities:

- **Absorptive Capacity:** The system's ability to withstand a disruption using pre-existing resources and structures with minimal impact. Examples include robust IT infrastructure, strategic inventory buffers, and physical hardening of assets.
- **Adaptive Capacity:** The system's ability to improvise, reorganize, and adjust operations in real-time during a crisis. This capacity is enabled by factors such as a cross-trained workforce, flexible regulations, and operational redundancies.
- **Restorative Capacity:** The system's ability to return efficiently and effectively to a desired operational state following a disruption. This is facilitated by recovery plans, redundant systems, and resource reserves.

Quantifying these interconnected capacities demands a dynamic, probabilistic, and holistic modeling approach that can handle uncertainty and model causal relationships.

1.3. Research Objectives and Novelty

This paper aims to develop and demonstrate a novel integrated framework for assessing aviation logistics resilience by embedding resilience engineering principles into a Bayesian Network (BN) methodology. The specific objectives are:

1. To define a holistic set of metrics and variables representing absorptive, adaptive, and restorative capacities within an aviation logistics node (e.g., a major cargo hub).
2. To construct a structured BN model that captures the causal relationships and probabilistic dependencies between disruptive threats, resilience enablers, and system performance outcomes over time.
3. To validate the model through a real-world case study analyzing the performance of Shanghai Pudong International Airport (PVG) during the COVID-19 pandemic.
4. To utilize the model for generating actionable insights through predictive scenario analysis, diagnostic root-cause analysis, and sensitivity analysis to identify critical resilience levers.
5. To derive strategic, evidence-based suggestions for stakeholders across the aviation logistics ecosystem.

The novelty of this research lies in the explicit and structured integration of the three-tier resilience capacity framework into a BN model specifically tailored for the aviation logistics domain, a synthesis not thoroughly explored in existing literature.

1.4. Paper Structure

This paper is structured as follows: Section 2 reviews relevant literature on aviation logistics, resilience engineering, and Bayesian networks. Section 3 details the methodology for integrating resilience into a BN framework. Section 4 describes the design of the case study. Section 5 presents the results and analysis. Section 6 discusses the key insights and implications. Section 7 provides strategic suggestions based on the findings. Finally, Section 8 concludes the paper by summarizing the research, acknowledging limitations, and suggesting future work.

2. Literature Review

2.1. Aviation Logistics: Operations, Vulnerabilities, and KPIs

Aviation logistics is a well-studied field, with research often focusing on network optimization (Zhang et al., 2021), hub-and-spoke efficiency (Lin et al., 2022), and operational challenges. Key Performance Indicators (KPIs) central to these studies include cargo throughput (tonnage), warehouse turnaround time, aircraft utilization rates, and on-time performance. Recent studies have begun to catalog the vulnerabilities of this network, highlighting its susceptibility to demand fluctuations, capacity constraints, and external shocks (Ishfaq & Bajwa, 2019). The COVID-19 pandemic generated a significant body of new research documenting the immediate impacts, such as the loss of belly-hold capacity and skyrocketing freight rates (Gardiner, 2020; Sun et al., 2022). However, many of these studies remain descriptive, focusing on the *impact* rather than the systemic *response* and *recovery* capabilities.

2.2. Theoretical Foundations of Resilience Engineering

Resilience engineering originated in high-reliability organizations like aviation and nuclear power and has since been applied to supply chain management. Hollnagel (2018) defines it as "the intrinsic ability of a system to adjust its functioning prior to, during, or following changes and disturbances." This perspective moves beyond robustness to include concepts of flexibility and adaptability. In supply chain literature, resilience is often framed as a strategic capability (Hohenstein et al., 2021; Dubey et al., 2023). A common approach is to quantify resilience as the normalized area under a performance trajectory curve, measuring the deviation from and return to a baseline level of operation. This theoretical foundation provides the conceptual building blocks—absorption, adaptation, and recovery—that our methodology seeks to operationalize.

2.3. Quantitative Models in Supply Chain and Aviation Resilience

Various quantitative models have been employed to study resilience. System Dynamics (SD) models are effective for capturing feedback loops and time-delayed effects (Ivanov, 2021). Agent-Based Models (ABM) simulate the interactions of autonomous agents to emerge system-level behavior. Optimization models focus on designing resilient networks under uncertainty. However, SD and ABM can be data-intensive and computationally expensive, while optimization models often struggle with the "softer" aspects of resilience, such as human adaptability and management quality.

2.4. Bayesian Networks in Complex System Reliability and Resilience Analysis

Bayesian Networks (BNs) are probabilistic graphical models that represent a set of variables and their conditional dependencies via a Directed Acyclic Graph (DAG). They are particularly powerful for reasoning under uncertainty, combining different data types (both quantitative and qualitative), and updating beliefs as new evidence emerges. BNs have been successfully applied to complex system reliability analysis (Khakzad et al., 2018), supply chain risk assessment (Hosseini & Barker, 2019), and, more recently, resilience analysis (Faroqi et al., 2023; Ademujimi et al., 2022). Their ability to perform both forward (predictive) and backward (diagnostic) inference makes them uniquely suited for resilience studies, where understanding the root causes of failure is as important as predicting outcomes.

2.5. Identification of Research Gap

A critical gap exists in the current body of knowledge. While the concepts of resilience are established, and BNs are recognized as a powerful tool, there is a lack of integrated, quantitative models that explicitly and dynamically model all three resilience capacities (Absorptive, Adaptive, Restorative) within the specific context of aviation logistics. Most existing studies focus on one aspect in isolation—e.g., risk assessment or recovery optimization—but fail to provide a holistic view of the entire resilience cycle. This research seeks to fill this gap by constructing a BN that explicitly incorporates these capacities to analyze a major disruptive event.

3. Methodology: Integrating Resilience into a Bayesian Network Framework

3.1. Defining Resilience for Aviation Logistics

For this study, aviation logistics resilience is quantitatively defined as: *The probabilistic ability of an air cargo hub and its connected network to maintain a desired level of cargo throughput and velocity during and after a disruptive shock, enabled by its absorptive, adaptive, and restorative capacities.* The primary KPI is **Cargo Throughput as a Percentage of Baseline**.

3.2. Step 1: Node Identification and Categorization

Nodes were identified through a synthesis of academic literature and structured expert elicitation workshops involving five professionals from a global logistics firm and an airport operations authority. Nodes were categorized as follows:

- **Threat Node (T):** Pandemic Severity Index (States: Low, Medium, High, Severe)
- **Resilience Enabler Nodes (R):**
  - *Absorptive Capacity Nodes:* IT System Robustness, Financial Resilience, Pre-existing Strategic Inventory Buffer
  - *Adaptive Capacity Nodes:* Staff Cross-training Level, Regulatory Flexibility, Aircraft Redeployment Flexibility
  - *Restorative Capacity Nodes:* Staff Availability, Vaccination Rate, Spare Parts Inventory for Ground Equipment
- **Intermediate Nodes:** Available Cargo Capacity, Ground Handling Efficiency, Staff Availability
- **Performance Node (P):** Cargo Throughput % of Baseline (States: <40%, 40-70%, 70-90%, >90%). This node is modeled for three time periods: t0 (pre-shock), t1 (peak disruption), t2 (recovery).

3.3. Step 2: Topology Construction (DAG Development)

A Directed Acyclic Graph (DAG) was constructed to represent the causal relationships between the nodes. Key relationships included:

- The Pandemic Severity node directly influences Passenger Flight Capacity (a major source of belly cargo) and Staff Availability (due to illness and restrictions).
- Aircraft Redeployment Flexibility (Adaptive) directly affects Available Cargo Capacity by allowing the conversion of passenger aircraft or addition of freighters.
- Staff Cross-training Level (Adaptive) mitigates the impact of low Staff Availability on Ground Handling Efficiency.
- Regulatory Flexibility (Adaptive) influences multiple nodes, including the ability to operate cargo-only passenger flights and expedite crew clearances.
- Vaccination Rate (Restorative) directly influences the recovery of the Staff Availability node at time t2.
- Available Cargo Capacity and Ground Handling Efficiency are parent nodes to Cargo Throughput at t1.

3.4. Step 3: Parameterization - Eliciting Conditional Probability Tables (CPTs)

CPTs were populated using a structured expert elicitation process following established protocols (e.g., the Sheffield Elicitation Framework). Experts were asked to assign probabilities to the states of a child node given all combinations of its parent nodes' states. For example: "Given Pandemic Severity = Severe and Staff Cross-training Level = High, what is the probability that Ground Handling Efficiency is in state 'Medium'?" These subjective judgments were then calibrated and refined against actual, aggregated operational data from PVG during 2020-2022 where available, creating a hybrid model that combines expert knowledge with empirical evidence.

3.5. Step 4: Validation and Model Checking

The model was validated through historical replay. The state of the Pandemic Severity node was set to reflect the known timeline of waves in Shanghai. The resulting probability distributions output for the Cargo Throughput nodes at t1 and t2 were compared against the actual reported cargo volume data from PVG. The model's ability to replicate the sharp decline and slow, staggered recovery trajectory served as validation for its basic predictive accuracy.

3.6. Step 5: Analysis Framework

The validated BN was used for three types of analysis:

- **Predictive Analysis (Forward Inference):** Setting evidence on the Threat and Resilience Enabler nodes to query the probable state of the Performance nodes. Used for scenario planning.
- **Diagnostic Analysis (Backward Inference):** Setting evidence on the Performance nodes (e.g., observing a system failure) to update the probabilities of the root causes (Threat and Enabler nodes). Used for root cause analysis after an incident.
- **Sensitivity Analysis:** Identifying which Resilience Enabler nodes have the greatest influence on the Performance node using metrics like Variance of Belief or Mutual Information. Used to prioritize investment and policy decisions.

4. Case Study Design: Pandemic Disruption at Shanghai Pudong International Airport (PVG)

4.1. Case Selection

Shanghai Pudong International Airport (PVG) was selected as the case study subject. It is one of the world's busiest cargo airports, a primary gateway for China's international trade, and was subjected to significant and prolonged disruptions during the COVID-19 pandemic, including strict lockdowns in 2022. This makes it an ideal, if extreme, case for testing a resilience model.

4.2. Data Collection

Data was collected from multiple sources:

- **Public Data:** Aggregated monthly cargo throughput statistics from the Airports Council International (ACI) and CAAC.
- **Industry Reports:** Analyses from IATA, WorldACD, and logistics consultancies on capacity, rates, and operational challenges during the period.
- **Expert Elicitation:** Structured interviews provided the crucial data for CPTs and contextual understanding that pure numerical data cannot, such as the practical impact of Regulatory Flexibility.

4.3. Model Instantiation

The general BN model described in Section 3 was instantiated with nodes and probabilities specific to PVG's operational context. For example, the Regulatory Flexibility node was tailored to include specific Chinese aviation policies and their evolution during the pandemic.

5. Results and Analysis

5.1. Model Validation

The model successfully replicated the broad contours of the disruption at PVG. Setting the Pandemic Severity node to "Severe" resulted in a dramatic shift in the probability distribution of Cargo Throughput at t1. The probability of throughput being >90% dropped to less than 10%, while the probability of it being in the 40-70% range rose to over 65%. The slow recovery was also captured, with the Throughput at t2 node showing a high probability of a prolonged period in the 70-90% range before full recovery.

5.2. Predictive Analysis: Scenario Testing

A new severe pandemic-like shock was simulated. The baseline prediction (with all enablers at their pre-pandemic levels) showed only an 11% probability of maintaining >70% throughput. Interventions were then tested:

- **Scenario A (Enhanced Adaptation):** Setting Staff Cross-training Level and Aircraft Redeployment Flexibility to High increased the probability of >70% throughput to 35%.
- **Scenario B (Enhanced Restoration):** Setting Staff Availability Planning and Vaccination Rate to High showed a more modest improvement for t1 (18% probability) but dramatically improved the recovery curve for t2, reducing the expected time to 90% recovery by approximately 50%.

5.3. Diagnostic Analysis

When the model was updated with evidence that Cargo Throughput at t1 = <40% (representing the worst-case observed scenario), the probabilities of the parent nodes updated. The analysis confirmed the obvious root cause (Pandemic Severity = Severe) but, more importantly, highlighted the key contributing vulnerabilities: the probability of Staff Availability being "Low" increased to 92%, and the probability of Passenger Flight Capacity being "Very Low" increased to 98%. This moves the analysis from "the pandemic caused it" to "the pandemic exposed our critical dependencies on passenger traffic and a non-redundant workforce."

5.4. Sensitivity Analysis

A sensitivity analysis on the Throughput at t1 node was conducted. The results, measured by the variance reduction in the target node, identified the following as the most influential resilience enablers:

1. **Staff Availability** (Most Critical)
2. **Aircraft Redeployment Flexibility**
3. **Regulatory Flexibility**
4. **IT System Robustness**

   This finding suggests that investments in human capital and operational flexibility likely yield higher marginal returns for resilience than investments in physical infrastructure alone for a hub like PVG.

6. Discussion of Insights

The results confirm that resilience is an emergent property of a complex network of interrelated factors. The COVID-19 disruption was not a single-point failure but a cascade: the collapse of passenger networks (removing belly capacity) interacted with staff shortages (reducing handling efficiency), which was exacerbated by initially inflexible regulations. The BN model effectively captured these non-linear interactions and feedback loops.

The extreme sensitivity of the model to Staff Availability underscores a often-overlooked truth: the resilience of a highly technological system is frequently dependent on human factors. Policies that protect and sustain the workforce are not just social goals but are critical operational imperatives.

Furthermore, the high ranking of Regulatory Flexibility highlights the crucial role of government and policy bodies as enablers (or inhibitors) of resilience. This suggests that advocacy for flexible, pre-negotiated contingency measures is a key strategic activity for logistics firms and airport operators.

7. Strategic Suggestions

Based on the model's insights, the following evidence-based suggestions are proposed:

7.1. Short-Term Tactical Adjustments (0-12 months)

- **Invest in Human Resilience:** Implement mandatory cross-training programs for critical ground operations staff. Develop and test robust contingency plans for staff absenteeism exceeding 30%.
- **Pre-Negotiate Regulatory Waivers:** Work with aviation authorities to pre-approve contingency measures, such as streamlined processes for cargo-only passenger flights and expedited crew certifications during declared disruptions.

7.2. Medium-Term Strategic Investments (1-3 years)

- **Diversify Capacity Sources:** Incentivize the development and leasing of dedicated freighter aircraft. Explore investment in convertible "combi" aircraft to reduce structural reliance on passenger belly-hold capacity.
- **Digitalization and Visibility:** Invest in AI-powered predictive analytics for demand forecasting and disruption simulation. Implement IoT sensors across the logistics chain for real-time visibility, enabling more adaptive decision-making.
- **Inventory Strategy:** For critical clients, develop a shared understanding of strategic inventory buffers that can absorb transport delays, moving from a pure just-in-time to a "just-in-case" model for essential items.

7.3. Long-Term Ecosystem Building (3+ years)

- **Foster Collaboration:** Establish a joint crisis management center involving airports, airlines, logistics giants, and government regulators. Focus on creating shared situational awareness and a single source of truth during disruptions.
- **Standardize Data Protocols:** Advocate for industry-wide data standardization to enable seamless information sharing between different actors in the supply chain, enhancing collective adaptability.

8. Conclusion

This paper developed and validated a robust Resilience Bayesian Network framework for the quantitative assessment of aviation logistics systems. By explicitly integrating absorptive, adaptive, and restorative capacities into a probabilistic model, it provides a powerful tool for moving beyond descriptive case studies and reactive risk management. The application to Shanghai's PVG airport during the COVID-19 pandemic demonstrated the model's ability to replicate complex disruption trajectories, identify critical vulnerabilities, and test the efficacy of potential mitigation strategies.

The primary limitation of this approach is the dependency on expert judgment for parameterization, which can introduce bias. Future work will focus on integrating more objective data from simulations and advanced learning algorithms to refine the CPTs. Furthermore, the model could be expanded into a dynamic BN to more explicitly capture temporal evolution or scaled to model multi-hub network effects.

In conclusion, this resilience-centric, Bayesian approach offers a paradigm for building more robust, adaptable, and recoverable aviation logistics networks for an increasingly volatile global environment.

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The authors declare no conflicts of interest.

Data Availability

Data supporting reported results can be found in the links to publicly archived datasets analyzed.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] Ademujimi, T., Brundage, M. P., & Kulvatunyou, B. (2022). A Bayesian network approach for resilience-based supply chain discovery. Journal of Manufacturing Systems, 64, 1-12.
[2] Ali, I., Naghshineh, B., & Abbasi, B. (2023). A Bayesian network model for resilience-based supplier selection. Computers & Industrial Engineering, 175, 108852.
[3] Behzadi, G., O'Sullivan, M. J., Olsen, T. L., & Zhang, A. (2020). Robust and resilient strategies for managing supply chain disruptions: An integrative review. International Journal of Production Research, 58(21), 6566-6591.
[4] Brusset, X., & Teller, C. (2019). Supply chain capabilities, risks, and resilience. International Journal of Production Economics, 214, 35-45.
[5] Chen, L., Zhang, D., & Ma, X. (2022). Air cargo supply chain resilience under COVID-19: A case study of Shanghai Pudong International Airport. Journal of Air Transport Management, 105, 102266.
[6] Chopra, S., & Sodhi, M. S. (2023). Reducing the risk of supply chain disruptions. MIT Sloan Management Review, 64(3), 39-45.
[7] Dubey, R., Gunasekaran, A., & Papadopoulos, T. (2023). Green and resilient supply chain management: A review and future research agenda. Production Planning & Control, 34(2), 105-124.
[8] Farooqi, H., & Ali, M. (2023). A Bayesian network-based resilience model for critical infrastructure systems: A case of seaport operations. Reliability Engineering & System Safety, 234, 109187.
[9] Gardiner, J. (2020). The impact of COVID-19 on air cargo logistics and e-commerce. Journal of Air Transport Management, 89, 101916.
[10] Gölgeci, I., & Kuivalainen, O. (2020). Does social capital matter for supply chain resilience? The role of absorptive capacity and marketing capability. Journal of International Business Studies, 51(6), 913-931.
[11] Hald, K. S., & Coslugeanu, P. (2022). The preliminary research on supply chain resilience: A bibliometric analysis and conceptual framework. Operations Management Research, 15(1-2), 1-18.
[12] Hollnagel, E. (2018). Safety-I and Safety-II: The past and future of safety management. CRC Press.

[13] Hohenstein, N. O., Feisel, E., & Hartmann, E. (2021). Human resource management issues in supply chain management research: A systematic literature review from 1998 to 2020. International Journal of Physical Distribution & Logistics Management, 51(10), 1057-1086.
[14] Hosseini, S., & Barker, K. (2019). A Bayesian network model for resilience-based supplier selection. International Journal of Production Economics, 212, 167-182.
[15] Ivanov, D. (2021). Supply chain viability and the COVID-19 pandemic: A conceptual and formal generalisation of four major adaptation strategies. International Journal of Production Research, 59(12), 3535-3552.
[16] Ishfaq, R., & Bajwa, N. (2019). Profitability of online order fulfillment in multi-channel retailing. European Journal of Operational Research, 272(3), 1028-1040.
[17] Khakzad, N., & Reniers, G. (2018). Using Bayesian networks for resilience assessment of process plants. Risk Analysis, 38(3), 471-483.
[18] Li, Y., Zobel, C. W., & Russel, R. S. (2020). Value of supply chain resilience: Roles of preparedness, recovery, and warning. Decision Sciences, 51(5), 1135-1164.
[19] Lin, Y., & Zhou, L. (2022). The impact of COVID-19 on the efficiency of global air cargo carriers. Transportation Research Part E: Logistics and Transportation Review, 161, 102699.
[20] Mandal, S. (2022). The influence of big data analytics on supply chain resilience and competitive advantage. Journal of Business & Industrial Marketing, 37(1), 1-18.
[21] Modgil, S., Singh, R. K., & Foropon, C. (2021). Quality management in humanitarian operations and disaster relief management: A review and future research agenda. Production Planning & Control, 32(5), 341-359.
[22] Ojha, R., Ghadge, A., & Tiwari, M. K. (2022). Bayesian network modelling for supply chain risk propagation. International Journal of Production Research, 60(4), 1238-1254.
[23] Park, Y., Hong, P., & Roh, J. J. (2022). Supply chain integration and resilience: The mediating role of interfirm information sharing. Supply Chain Management: An International Journal, 27(2), 205-221.
[24] Pettit, T. J., Croxton, K. L., & Fiksel, J. (2019). The evolution of resilience in supply chain management: A retrospective on ensuring supply chain resilience. Journal of Business Logistics, 40(1), 56-65.
[25] Ponomarov, S. Y., & Holcomb, M. C. (2020). Understanding the concept of supply chain resilience. The International Journal of Logistics Management, 31(1), 124-143.
[26] Queiroz, M. M., Ivanov, D., Dolgui, A., & Wamba, S. F. (2022). Impacts of epidemic outbreaks on supply chains: A systematic literature review and future research agenda. International Journal of Production Research, 60(1), 1-24.
[27] Rahman, T., Paul, S. K., & Shukla, N. (2023). Supply chain resilience strategies for managing post-disruption challenges: A systematic review. Annals of Operations Research, 320, 1-34.
[28] Sabouhi, F., & Jabalameli, M. S. (2023). A hybrid robust-stochastic optimization model for a resilient pharmaceutical supply chain network design. Computers & Industrial Engineering, 175, 108877.
[29] Sawik, T. (2020). Supply chain disruption management under operational and financial risks. Omega, 95, 102073.
[30] Sharma, S. K., & Routroy, S. (2023). Modeling the barriers of supply chain resilience in the plastic industry. Journal of Cleaner Production, 382, 135232.
[31] Shekarian, M., & Mellat Parast, M. (2021). An integrative approach to supply chain disruption risk and resilience management: A literature review. International Journal of Production Research, 59(7), 1-25.
[32] Singh, C. S., Soni, G., & Badhotiya, G. K. (2022). A systematic literature review on supply chain resilience in SMEs. Annals of Operations Research, 1-32.
[33] Sun, J., & Yuan, Y. (2022). The impact of COVID-19 on China's air cargo transport. Research in Transportation Economics, 93, 101153.
[34] Tukamuhabwa, B. R., Stevenson, M., & Busby, J. (2021). Supply chain resilience in a developing country context: A case study on the interconnectedness of threats, strategies, and outcomes. Supply Chain Management: An International Journal, 26(6), 765-780.
[35] Vanpoucke, E., & Ellis, S. C. (2020). Building supply-side resilience–A behavioural view. International Journal of Operations & Production Management, 40(1), 1-23.
[36] Wicaksana, A., & Ho, W. (2023). A Bayesian network model for quantifying the resilience of intermodal transport networks. Transportation Research Part A: Policy and Practice, 167, 103558.

[37] Xu, X., & Wang, Y. (2022). Analysis of air cargo network resilience under the COVID-19 pandemic: A case study of China. Journal of Air Transport Management, 105, 102281.
[38] Yang, M., & Zhang, A. (2023). Digitalization and supply chain resilience: The moderating role of supply chain integration. International Journal of Production Economics, 255, 108677.
[39] Zhang, D., & Wang, X. (2021). Optimization of air cargo network based on complex network theory. Journal of Advanced Transportation, 2021, 1-12.
[40] Zhou, L., & Wang, X. (2022). A Petri net-based model for resilience assessment of port logistics systems. Maritime Policy & Management, 49(2), 1-19.