EGE SCHOLAR JOURNAL

Ege Scholar Journal, Year: 2025, Volume: 2, Issue: 3, Pages : 171-183 Research Article

DOI: 10.5281/zenodo.18525771

Publication Date: 30.09.2025

Gaurav Kumar[1]

1. ORCID: https://orcid.org/0000-0002-1800-3213 Email: klgaurav4@gmail.com KLEF Business School, KL University, India Vaddeswaram, Guntur District, Andhra Pradesh 522502, India

Design-Science Framework for Decision-Centric Supply Chain Resilience

Abstract

Geoeconomic shocks—including tariff escalations, sanctions, export controls, and commodity dislocations—have increased disruption frequency and exposed limitations of steady-state supply chain planning. This paper develops a design-science, governance-centred framework for resilient supply chain decision-making by synthesizing institutional resilience guidance and published empirical findings on analytics-enabled supply chain performance. The framework is operationalized as a modular operating model spanning (i) sensing and early warning, (ii) predictive disruption modelling under regime shifts, (iii) prescriptive optimization with human-in-the-loop controls, (iv) digital-twin simulation for scenario stress-testing, and (v) execution orchestration with auditability and compliance alignment. The paper provides an end-to-end reference architecture (Figure 1), a resilience analytics control matrix linking modules to prerequisites and governance controls (Table 1), and maturity-aligned implementation pathways with measurable resilience KPIs, including time-to-detect, time-to-decide, and time-to-recover. The findings emphasize that resilience improvements require both robust models and disciplined governance to ensure adoption and accountable execution.

Keywords: Supply chain resilience; Geoeconomic shocks; Artificial intelligence; Prescriptive analytics; Digital twins.

How to cite: Kumar G. (2025). Design-Science Framework for Decision-Centric Supply Chain Resilience. *Ege Scholar Journal, 2*(3), 171-183

Introduction

Geoeconomic conditions increasingly shape supply chain performance alongside, and often as strongly as, operational efficiency in the global economy. Trade policy uncertainty, tariffs, sanctions regimes, and industrial policy interventions now materially influence sourcing feasibility, transit routes, compliance requirements, and cost structures. Recent macroeconomic outlooks produced by international institutions emphasize that heightened trade tensions and policy uncertainty strain global supply chains by increasing production costs, delaying investment decisions, and reducing the predictability required for long-term planning. At the sectoral level, commodity and metals markets have experienced disruption- and tariff-related dislocations, amplifying input-cost volatility and procurement risk.These dynamics expose a structural mismatch between contemporary supply chain realities and classical planning systems. Traditional supply chain optimization models were largely designed for environments characterized by relatively stable trade regimes and limited disruption bandwidth. By contrast, current disruptions—including port congestion, rerouted shipping lanes, export controls, sudden tariff adjustments, energy price shocks, and supplier financial distress—are nonlinear in nature and can propagate rapidly across multi-tier networks. As a result, resilience has re-emerged as a central performance objective. In contemporary literature, resilience is commonly defined as the capacity to anticipate, absorb, adapt to, and recover from disruptions while maintaining acceptable service levels and cost performance.Importantly, policy and research communities increasingly stress that resilience should not be equated with autarky or indiscriminate reshoring. Instead, guidance emphasizes a balanced approach that mitigates supply chain risks without undermining the efficiency gains of international trade. Diversification strategies, trade facilitation measures, and strengthened analytical capacity are identified as key enabling conditions for resilient yet open supply chains.In practical terms, resilience constitutes an optimization problem under uncertainty. Organizations must detect shocks earlier, make decisions more rapidly under binding constraints, and execute coordinated recovery actions across functions and supply-chain tiers. This is the context in which advanced analytics and artificial intelligence have become strategically salient. Modern supply chains generate large volumes of heterogeneous data, including transactional demand signals, shipment events, supplier performance metrics, quality indicators, market prices, and external signals such as policy changes and logistics stress measures. However, data abundance alone does not ensure improved decision-making. Many organizations continue to face fragmented data architectures, inconsistent master data, and planning processes that inadequately represent uncertainty, regime shifts, or tail risks.Survey-based evidence from supply chain leaders indicates persistent gaps in risk identification and mitigation capabilities, often rooted in governance and operating-model constraints that limit the translation of analytical insights into operational action. Consequently, recent scholarship increasingly conceptualizes artificial intelligence not as a narrow automation tool, but as a resilience capability that spans pre-disruption preparation, in-disruption response, and post-disruption recovery. At the same time, AI-enabled resilience initiatives exhibit predictable failure modes. Models trained on historically stable regimes may degrade sharply under structural shocks; algorithmic recommendations may not be embedded in decision rights or escalation processes; and limited transparency can reduce user trust and adoption. Geoeconomic disruptions further complicate AI deployment by introducing constraints related to data sharing, supplier onboarding, and regulatory compliance, including sanctions screening, export controls, and traceability requirements. Against this backdrop, the central analytical question is no longer whether firms should deploy artificial intelligence in supply chain management, but rather which governance structures, data architectures, and decision frameworks are required for analytics to generate measurable improvements in resilience under conditions of persistent trade uncertainty.

Research objectives

This study pursues four objectives:

1. **Shock pathways and decision loci:** Conceptualize the principal geoeconomic shock pathways (e.g., tariffs, sanctions/export controls, trade fragmentation, and commodity dislocations) that degrade supply chain performance, and identify the corresponding decision points where analytics can generate resilience leverage.

2. **Operating-model translation:** Translate institutional resilience guidance—particularly on diversification, monitoring, trade facilitation, and analytical capacity—into a firm-level, governance-centred operating model for analytics-enabled resilience.

3. **Reference architecture and controls:** Develop an end-to-end reference architecture (Figure 1) and a resilience analytics control matrix (Table 1) that links analytics modules to resilience mechanisms, governance controls, and measurable outcomes.

4. **Implementation and measurement:** Propose maturity-aligned implementation pathways and a resilience measurement system using outcome and process KPIs (e.g., service performance under disruption, cost-to-serve, and time-to-detect/time-to-decide/time-to-recover).

Contribution

This paper contributes a design-science, governance-centred framework for resilient supply chain decision-making. First, it links analytics capabilities—such as sensing and anomaly detection, regime-aware forecasting, prescriptive optimization, and digital-twin simulation—to explicit resilience mechanisms, including visibility, optionality, decision velocity, and coordinated recovery. Second, it translates high-level institutional resilience guidance into an implementable operating model by specifying decision rights, control points, and auditability requirements needed to convert analytics outputs into accountable actions. Third, it operationalizes resilience measurement by aligning macro-level stress monitoring concepts with firm-level outcome and process KPIs, enabling trigger-based escalation and post-incident learning loops. Collectively, the paper provides an end-to-end reference architecture (Figure 1) and a resilience analytics control matrix (Table 1) intended to support implementation planning and empirical evaluation in organizational settings.

Materials and Methods

Study Design

This study adopts a **design-science and applied-systems synthesis** to develop an implementable framework for resilient supply chain decision-making under geoeconomic shocks. The method proceeds in four steps:

1. **Problem framing and construct definition:** Define geoeconomic shock pathways and specify the resilience outcome space (service, cost, and recovery performance) and the enabling capability set (visibility, optionality, decision velocity, and recovery orchestration).

2. **Evidence synthesis:** Integrate institutional guidance and monitoring approaches with published academic findings and established practitioner patterns to identify recurring design requirements for analytics-enabled resilience.

3. **Framework construction:** Translate requirements into a modular operating model and governance-centred reference architecture (Figure 1), including decision rights, control points, and auditability requirements.
4. **Operationalization and evaluation logic:** Derive a control matrix (Table 1) linking analytics modules to prerequisites, governance controls, and expected resilience effects, and specify a measurement system and maturity-aligned implementation pathways.

Data Sources

Evidence was drawn from three categories of sources.

1. **Policy and institutional sources** (resilience definitions, enabling conditions, and monitoring constructs):
    - OECD guidance on resilience policy tools, monitoring, digitalization, and analytical capacity.
    - World Bank monitoring constructs for global supply chain stress and macro-logistics disruption.
    - United Nations macroeconomic outlooks describing trade tensions, policy uncertainty, and their implications for supply chains.
    - USTR guidance on conceptualizing and measuring supply chain resilience.
    - World Bank global outlook material contextualizing trade fragmentation and growth risks.
2. **Academic and technical literature** (peer-reviewed studies and syntheses on AI/analytics and resilience):
    - Empirical studies examining associations between AI adoption and resilience performance across preparation, response, and recovery phases.
    - Research agendas and conceptual papers on prescriptive analytics and resilience operating models.
    - Recent systematic literature reviews on AI applications in supply chain management, risk analytics, and resilience.
3. **Practitioner architecture references** (implementation patterns, operating models, and digital twin adoption):
    - Practitioner materials on analytics operating models in supply chain and procurement.
    - Digital twin implementation patterns for end-to-end supply chains.

Source handling note (for rigor): Institutional and practitioner sources were used to derive implementation constraints and governance patterns, while academic sources were used to substantiate mechanisms and measurement constructs. Full bibliographic details are provided in the reference list.

Analytical Framework

Resilience is operationalized through four capabilities:

- **Visibility (V):** early detection of disruptions using integrated internal and external signals.
- **Optionality (O):** feasible switching across suppliers, routes, modes, and inventory policies under constraints.
- **Decision velocity (D):** speed of scenario evaluation and decision selection under uncertainty.
- **Recovery orchestration (R):** coordinated execution of recovery actions across functions and tiers.

AI/analytics modules are evaluated against these capabilities using the following criteria:

- **C1 — Performance effect:** expected impact on service and/or cost under disruption (e.g., OTIF, fill rate, cost-to-serve).
- **C2 — Data feasibility:** availability and quality of required internal/external data, including master data integrity.
- **C3 — Shock robustness:** robustness under distribution shift, including drift detection and revalidation needs.
- **C4 — Adoption and accountability:** explainability and human-in-the-loop decision integration.
- **C5 — Governance and compliance alignment:** traceability, audit trails, and trade-compliance constraints.

Measurement Approach

The measurement system includes:

- **Outcome KPIs:** fill rate; OTIF (on-time in-full); lead-time variability and tail risk; cost-to-serve; revenue at risk; and **time-to-recover (TTR)**.
- **Process KPIs:** forecast bias and drift under shocks; alert precision/false-positive rate; scenario cycle time (time-to-decide); override rates and execution adherence.
- **Context indicators:** external stress proxies (e.g., global stress indices and commodity volatility) used to contextualize performance and trigger escalation modes.

Limitations

This study is a **design-science, applied synthesis** rather than a firm-level causal econometric analysis. Accordingly, the proposed architecture, control matrix, and implementation pathways are presented as **design propositions** grounded in prior literature and institutional guidance, not as statistically identified causal effects. The framework's performance implications are therefore contingent on organizational context, including data maturity, process standardization, and governance capability. In addition, the analysis does not quantify the incremental contribution of individual modules (e.g., forecasting vs. optimization) or the general-equilibrium effects of trade policy regimes. Future work should evaluate the propositions through (i) controlled pilots and A/B comparisons on operational KPIs (e.g., OTIF under disruption, cost-to-serve, time-to-recover), (ii) quasi-experimental designs where feasible, and (iii) multi-case replications across industries to strengthen external validity.

Results

Figure 1. AI-and-Analytics Resilience Architecture for Post-Shock Supply Chains

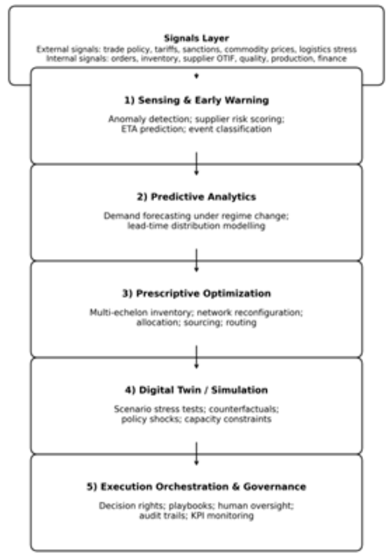

Figure 1. Reference architecture for analytics-enabled supply chain resilience. The architecture forms a control loop from sensing to governed execution.

Interpretation. Figure 1 presents a modular resilience "control loop" that integrates external geoeconomic signals with internal operational telemetry. The design progresses from early warning to predictive modelling, prescriptive decision support, scenario simulation, and governed execution. The architecture emphasizes that measurable resilience depends on both analytical accuracy and operating-model controls—decision rights, auditability, and KPI-based learning loops.

Table 1 (mandatory)

Table 1. Resilience analytics modules: prerequisites, governance controls, and expected impact

Module	Primary AI/analytics methods	Minimum prerequisites	Key governance controls	Expected resilience impact
Sensing & early warning	Anomaly detection; NLP event tagging; supplier risk scoring; ETA prediction	Event data; supplier master data; external feeds; alert taxonomy	Alert thresholds; false-positive review; ownership and escalation rules	↑ Visibility; ↓ time-to-detect
Predictive disruption modelling	Regime-switch forecasting; lead-time distribution modelling; causal feature engineering	Historical data with shock periods; feature store; baseline models	Drift monitoring; shock backtesting; calibration checks	↑ Decision quality; ↓ bullwhip
Prescriptive optimization	Stochastic programming; robust optimization; constrained RL (optional)	Constraints model; cost-to-serve; service targets; feasible action set	Human approval gates; explainable recommendations; override logging	↑ Optionality; ↓ cost-to-serve
Digital twin simulation	Network simulation; scenario stress tests; counterfactual analysis	Network graph; capacities; service rules; scenario library inputs	Scenario catalog governance; model validation; periodic re-baselining	↑ Preparedness; faster recovery
Orchestration & governance	Dashboards; playbooks; workflow automation; audit logging	Decision rights; SOPs; KPI system; incident review process	Audit trails; post-incident reviews; retraining triggers; compliance checks	↑ Decision velocity; ↑ recovery coordination

Interpretation. Table 1 links each analytics module to the minimum data and operating prerequisites, the governance controls required to ensure accountable adoption, and the expected resilience effects. This mapping is intended to support implementation planning and evaluation by connecting technical design choices to measurable resilience outcomes.

3.1 Post-shock resilience mechanisms enabled by AI (Revised)

AI can strengthen supply chain resilience through three complementary mechanisms that map directly to the modular architecture in Figure 1 and the governance/control requirements summarized in Table 1.

Mechanism 1: Signal amplification under uncertainty (visibility and early detection). During geoeconomic shocks, conventional lagging indicators (e.g., monthly performance reports or periodic supplier reviews) are often too slow to support timely intervention. AI-enabled sensing integrates external signals—such as policy announcements, logistics stress, and commodity price dislocations—with internal operational telemetry to detect early deviations, emerging bottlenecks, and tier-specific vulnerabilities. In practice, firms can complement macro-level stress monitoring with internal "firm stress indices" that combine lead-time dispersion, capacity utilization, supplier reliability, and event-based exceptions to trigger escalation modes and predefined playbooks.

Mechanism 2: Predictive adaptation across resilience phases (robust forecasting and risk anticipation). Resilience is dynamic across preparation, response, and recovery. Under regime shifts, models calibrated on stable periods can degrade rapidly, and point forecasts can become systematically biased. Predictive disruption modelling therefore focuses on regime-aware forecasting and lead-time distribution modelling, supported by drift monitoring and shock backtesting. This mechanism improves decision quality by converting raw signals into quantified risk and uncertainty estimates that downstream optimization and scenario planning can use, rather than relying on single-number forecasts.

Mechanism 3: Prescriptive action selection and rapid reconfiguration (optionality and execution readiness). Prescriptive analytics converts predictions into decisions: sourcing reallocations, inventory positioning, allocation controls, and routing choices under explicit constraints. Digital twins reinforce this mechanism by enabling fast scenario evaluation, counterfactual analysis, and policy-shock stress testing—particularly for network reconfiguration decisions where second-order effects (capacity, lead-time tails, compliance constraints) matter. Critically, this mechanism depends on governance: approval gates, explainable recommendations, and auditable decision trails ensure that prescriptive outputs translate into accountable actions rather than remaining advisory artefacts.

3.1.1 Implementation pathways under varying maturity (Revised)

To support adoption across heterogeneous capability levels, we propose three maturity-aligned implementation pathways consistent with the module sequencing in Figure 1 and the control matrix in Table 1.

Path A — Foundational visibility (data and early warning).

Organizations should begin by unifying event ingestion, improving master data quality (supplier, item, lane, site), and deploying early-warning alerts with defined ownership and escalation rules. The objective is to reduce time-to-detect and establish reliable telemetry before introducing more complex optimization or simulation components.

Path B — Decision intelligence (predictive + governed prescriptive).

With a stable data foundation, firms can layer predictive models for lead-time distribution shifts and demand regime changes, embed systematic backtesting on shock periods, and introduce prescriptive optimization within a controlled decision process. Guardrails—such as human-in-the-loop approvals, policy constraints, and override logging—are essential to maintain trust and compliance while increasing decision speed and reducing cost-to-serve under stress.

Path C — Constrained orchestration (digital twins and workflow integration).

Mature organizations can integrate digital twins for scenario-based planning and incorporate workflow automation for faster execution, while keeping high-impact and compliance-sensitive decisions human-approved. This pathway emphasizes operationalizing learning loops: post-incident reviews, retraining triggers, and scenario catalog governance to prevent model brittleness and institutionalize continuous improvement.

Across all pathways, resilience measurement should be anchored to repeatable KPIs—time-to-detect, time-to-decide, and time-to-recover—alongside service performance under disruption (e.g., OTIF/fill rate) and cost outcomes (e.g., cost-to-serve). External stress proxies and trade-policy uncertainty indicators can be used to contextualize results and justify trigger-based operating modes.

Numbered list (edited for academic consistency)

1. **Define a shock taxonomy:** tariffs, sanctions/export controls, commodity spikes, route disruptions, and supplier insolvency.
2. **Establish a resilience data product:** unified event model, master-data governance, and external signal connectors.
3. **Build a risk model library:** supplier risk scoring, lead-time shift detection, and demand regime-switching models.
4. **Adopt prescriptive playbooks:** pre-approved actions by shock type (reallocate, expedite, dual-source, substitute).
5. **Deploy digital twin stress tests:** simulate policy shocks and capacity loss; quantify service and cost impacts.
6. **Implement governance gates:** human-in-the-loop approvals for strategic sourcing, compliance-sensitive trades, and pricing.
7. **Measure resilience continuously:** time-to-detect, time-to-decide, time-to-recover; link metrics to business outcomes.
8. **Run post-incident learning loops:** root-cause analysis, retraining triggers, supplier requalification, and policy updates.

Discussion

Geoeconomic shocks as structural uncertainty

Geoeconomic disruptions differ fundamentally from conventional forms of operational variability because they can reprice entire sourcing strategies and network configurations through legal and policy constraints, including sanctions regimes, export controls, and heightened compliance requirements, as well as through abrupt cost shocks such as tariffs and commodity-market dislocations. Unlike routine demand or supply fluctuations, these shocks alter the feasible set of suppliers, routes, and contractual relationships rather than merely increasing variance around existing baselines.International macroeconomic assessments consistently indicate that heightened trade tensions and policy uncertainty weaken growth prospects, raise production costs, and place sustained strain on global supply chains. These conditions reinforce the necessity of planning under structural uncertainty rather than assuming stationary stochastic disturbances that can be managed through historical averages or marginal buffers.Within this environment, resilience strategies that rely primarily on backward-looking indicators or single-regime planning assumptions are likely to underperform. When disruption dynamics shift rapidly across legal, economic, and logistical dimensions, effective resilience requires adaptive planning frameworks capable of accommodating regime changes, constraint redefinitions, and non-linear propagation effects across multi-tier supply networks.

Why analytics improves resilience only with governance and adoption

Although AI models can detect patterns and anomalies faster than human analysts, they do not automatically translate into decisions or coordinated execution. The framework in Figure 1 and the control matrix in Table 1 therefore treat governance as a first-class design requirement: resilience architectures must specify (i) who has decision rights to act on signals, (ii) what actions are permissible under policy, cost, and compliance constraints, and (iii) how decisions are audited, reviewed, and improved. This emphasis is consistent with institutional guidance that highlights analytical capacity and digitalization as enabling conditions, while also warning that resilience cannot be achieved through simplistic structural moves alone. From an implementation standpoint, adoption mechanisms (explainability, approval gates, override logging, and post-incident reviews) are not ancillary controls; they are the means by which analytical outputs become accountable operating decisions.

Digital twins and scenario discipline

Digital twins are particularly valuable under geoeconomic shocks because they enable disciplined "what-if" assessments of tariffs, route changes, and supplier loss under capacity, service, and compliance constraints. In the proposed architecture, the digital-twin layer supports counterfactual evaluation and stress testing, but its effectiveness depends on scenario governance: firms should maintain a curated scenario catalog linked to playbooks, KPI thresholds, and retraining triggers. Without this discipline, scenario planning can devolve into ad hoc modelling that is difficult to reproduce, validate, or operationalize.

Policy alignment: diversification versus localization

The framework aligns with OECD resilience perspectives that emphasize strengthening and diversifying supply chains while avoiding approaches that undermine the gains from open trade. OECD reporting cautions that simply re-localising production within national borders can harm growth and may not reliably strengthen resilience.For firms, the implication is analytics-driven diversification: multi-sourcing, selective nearshoring where justified, and dynamic allocation under uncertainty, rather than static relocation. Prescriptive analytics and simulation can make these trade-offs explicit by quantifying service, cost, and compliance impacts across alternative network configurations.

Measuring resilience credibly

Credible resilience management requires measurement systems that are sensitive to stress regimes and comparable over time. Macro-level monitoring tools such as the World Bank's Global Supply Chain Stress Index illustrate how stress can be quantified using shipping and logistics signals derived from tracking data, and can be used as an exogenous contextual indicator when interpreting firm performance.At the firm level, analogous indices can be constructed by combining lead-time dispersion (including tail risk), supplier reliability, event exception rates, and capacity utilization. These indices enable trigger-based governance: when stress crosses thresholds, organizations can transition into predefined operating modes (e.g., allocation controls, inventory buffers, alternative routing) and subsequently evaluate effectiveness through time-to-detect, time-to-decide, and time-to-recover metrics.

Limits and risks

AI introduces non-trivial risks for resilience programs. Models can become brittle under regime shifts, early-warning systems can create alert fatigue through false positives, and prescriptive optimizers can overfit cost objectives in ways that reduce slack and adaptability. In geoeconomic contexts, additional risks arise from compliance obligations (sanctions/export controls/traceability), which can conflict with purely cost-minimizing recommendations. Therefore, analytics must be embedded within compliance-aware workflows and must produce auditable evidence—data lineage, assumptions, constraints, and rationale—for why specific actions were recommended and approved. This reinforces the paper's central claim: resilience depends not only on analytical capability, but on governance mechanisms that ensure accountable adoption and continuous learning.

Conclusions

AI and advanced analytics can materially strengthen supply chain resilience under geoeconomic shocks, but only when deployed as a governed, end-to-end decision system rather than as isolated predictive models. The paper's central contribution is a modular architecture (Figure 1) that connects sensing and early warning, predictive disruption modelling, prescriptive optimization, and digital-twin simulation to execution orchestration with clear decision rights, auditability, and KPI-based learning loops. The accompanying control matrix (Table 1) operationalizes implementation by specifying minimum prerequisites, governance controls, and expected resilience effects for each module.The synthesis further indicates that resilience improvements are driven by lifecycle integration across preparation, response, and recovery, particularly under regime shifts where models calibrated on stable periods can degrade. Accordingly, the recommended strategy is maturity-aligned: organizations with fragmented data should begin with reliable telemetry and early-warning controls; those with stable data foundations should extend to regime-aware forecasting and governed prescriptive decision support; and mature organizations can integrate digital twins and constrained automation to accelerate scenario evaluation and execution while maintaining human oversight for high-impact or compliance-sensitive decisions.Finally, resilience should be managed through measurable KPIs—time-to-detect, time-to-decide, and time-to-recover—alongside service and cost outcomes under disruption. In an environment characterized by trade tensions and policy uncertainty, these capabilities constitute a strategic operating requirement rather than an optional technology initiative.

Patents (Revised)

This manuscript does not claim a patentable invention. However, the proposed architecture may inform proprietary implementations, including event-driven resilience signal engines, supplier risk scoring integrated with trade-compliance screening, digital-twin platforms incorporating tariff and route-shock scenarios, and prescriptive optimizers with explainable policy constraints. Potentially patentable outcomes would most plausibly arise from novel shock-aware optimization formulations, privacy-preserving multi-tier data sharing methods, or automated governance workflows that link alerts to auditable approvals and execution traces.

Supplementary Materials (Revised)

Supplementary materials may include: (i) a canonical supply chain event schema for disruption sensing; (ii) a feature dictionary for supplier risk scoring and lead-time shift detection; (iii) a scenario catalog template for trade-policy and logistics shocks (tariff escalation, sanctions/export controls, route disruption, capacity loss); (iv) a playbook library mapping triggers to pre-approved actions; and (v) a dashboard specification for resilience KPIs (e.g., time-to-detect/time-to-decide/time-to-recover, OTIF under disruption, and cost-to-serve).

Author Contributions (Revised – standard CRediT-style wording)

Conceptualization: G.K.; Methodology: G.K.; Formal analysis: G.K.; Investigation: G.K.; Writing—original draft: G.K.; Writing—review and editing: G.K.; Visualization: G.K.; Supervision: Not applicable; Project administration: Not applicable. The author is responsible for the integrity of the synthesis and for the accuracy of the cited sources.

Funding (Revised)

No external funding was received for this study. Future extensions—particularly empirical evaluation using firm-level operational data, quasi-experimental designs where feasible, or multi-site replications—may require funding to support secure data infrastructure, model monitoring, and independent evaluation.

Institutional Review Board Statement (Revised)

Not applicable. This study synthesizes publicly available institutional sources and published literature and does not involve human participants, interventions, or identifiable personal data. If future work includes interviews, surveys, or analysis of proprietary datasets containing personal or sensitive information, appropriate ethics review and data protection procedures should be implemented.

Informed Consent Statement (Revised)

Not applicable. No human subjects were recruited and no personal data were collected. If future studies involve human participants (e.g., expert interviews or experiments), informed consent should be obtained in accordance with applicable institutional policies.

Acknowledgments (Revised)

The author acknowledges the availability of international institutional publications and datasets that support systematic analysis of trade conditions, logistics stress, and resilience policy design. The author also acknowledges the supply chain and operations research community for advancing methods in resilience measurement, prescriptive analytics, and decision-support systems.

Conflicts of Interest (Revised)

The author declares no conflicts of interest. The author has no financial or personal relationships with AI software vendors, logistics providers, or consulting organizations that could be perceived as influencing the results or conclusions of this study.

Appendix A

Appendix A. Resilience Readiness Checklist (condensed)

A1. Master data quality (suppliers, items, sites, lanes) and unique identifiers
A2. Event ingestion coverage (shipments, ETAs, port status, orders, inventory)
A3. External signal feeds (trade policy, tariffs, commodity prices, stress indicators)
A4. Model governance (registry, ownership, drift monitoring, retraining triggers)
A5. Scenario catalog and playbooks mapped to decision rights
A6. Optimization constraints documented, reviewed, and auditable
A7. KPI dashboard (TTR, OTIF under shock, cost-to-serve)
A8. Post-incident learning loop (root-cause analysis, corrective actions, supplier strategy updates)

Appendix B

Appendix B. Monitoring Dashboard Indicators (condensed)

B1. Time-to-detect disruption (hours/days)
B2. Time-to-decide (scenario cycle time)
B3. Time-to-recover (TTR) by product family/region
B4. Lead-time variance and tail risk (e.g., 95th percentile lead time)
B5. Service level under stress (fill rate, OTIF)
B6. Alert precision/recall (false-positive rate)
B7. Optimization adherence and override rates
B8. Internal resilience stress index (composite indicator benchmarked against external stress proxies)

References

1. Organisation for Economic Co-operation and Development. (2025). *OECD supply chain resilience review: Navigating risks*. OECD Publishing.

2. World Bank. (n.d.). *Global Supply Chain Stress Index (GSCSI)*.

3. World Bank. (2025). *Global economic prospects* (June 2025). World Bank.

4. United Nations, Department of Economic and Social Affairs. (2025). *World economic situation and prospects 2025*. United Nations.

5. Office of the United States Trade Representative. (2024). *Adapting trade policy for supply chain resilience*.

6. Tang, H., Wu, K., & Zhou, J. (2025). Smarter supply chains, stronger resilience? The impact of AI on preparation, response, and recovery. *Economics Letters*, 254, 112488.

7. Smyth, C., Dennehy, D., Wamba, S. F., Scott, M., & Harfouche, A. (2024). Artificial intelligence and prescriptive analytics for supply chain resilience: A systematic literature review and research agenda. *International Journal of Production Research*, 62(23), 8537–8561.

8. Teixeira, A. R., Ferreira, J. V., & Ramos, A. L. (2025). Intelligent supply chain management: A systematic literature review on artificial intelligence contributions. *Information*, 16(5), 399.

9. Jahin, M. A., Naife, S. A., Saha, A. K., & Mridha, M. F. (2024). AI in supply chain risk assessment: A systematic literature review and bibliometric analysis. *arXiv Working Paper*.

10. Alicke, K., Oca, A., Somekh, A., & Biswas, S. (2025). Beyond automation: How generative AI is reshaping supply chains. *McKinsey & Company*.

11. McKinsey & Company. (2024). *Digital twins: The key to unlocking end-to-end supply chain growth*.

12. McKinsey & Company. (2024). *Supply chain risk survey 2024: Global supply chain leader survey*.

13. Arvis, J.-F., Rastogi, C., Rodrigue, J.-P., & Ulybina, D. (2024). A metric of global maritime supply chain disruptions: The Global Supply Chain Stress Index (GSCSI). *World Bank Policy Research Working Paper*.

14. Horne, A. (2025). Disruption and dislocation: LME metals' year in seven charts. *Reuters*.

15. Financial Times. (2025). Aggressive reshoring of supply chains risks significant GDP loss, warns OECD. *Financial Times*.

16. Council of Economic Advisers. (2023). *Issue brief: Supply chain resilience*. The White House.

17. Mittal, A., Cocoual, C., Erriquez, M., & Liakopoulou, T. (2024). Revolutionizing procurement: Leveraging data and AI for strategic advantage. *McKinsey & Company*.

18. Daci, E., & Rexhepi, B. R. (2024). The role of management in microfinance institutions in Kosovo: Case study of the Dukagjini region. *Quality – Access to Success*, 25(202), 207–213.

19. Murtezaj, I. M., Rexhepi, B. R., Dauti, B., & Xhafa, H. (2024). Mitigating economic losses and prospects for the development of the energy sector in the Republic of Kosovo. *Economics of Development*, 23(3), 82–92.

20. Murtezaj, I. M., Rexhepi, B. R., Xhaferi, B. S., Xhafa, H., & Xhaferi, S. (2024). The study and application of moral principles and values in the fields of accounting and auditing. *Pakistan Journal of Life and Social Sciences*, 22(2), 3885–3902.