International Journal of Engineering Research and Development
e- ISSN: 2278-067X, p-ISSN: 2278-800X, www.ijerd.com
Volume 22, Issue 3 (March 2026), PP 109-120

Supply Chain Resilience in the Age of Global Disruptions: AI-Driven Risk Modeling and Optimization Frameworks for Climate, Conflict, and Pandemic Shocks

Udu Chukwudi Emeka, Okpala Charles Chikwendu and OnukwuliSomto Kenneth
Industrial/Production Engineering Department, Nnamdi Azikiwe University, Awka - Nigeria.

Abstract
Global supply chains are increasingly exposed to overlapping and systemic disruptions which arise from climate change, geopolitical conflicts, and pandemics, thereby challenge traditional risk management and sustainability strategies. Recent crises have revealed that reactive and static resilience approaches often exacerbate environmental impacts while failing to ensure continuity under compound shocks. This study proposes an integrated AI-driven risk modeling and optimization framework that is designed to enhance supply chain resilience, while delivering measurable sustainability benefits. The framework combines machine learning-based disruption forecasting using climate hazard indicators, conflict event dynamics, and pandemic-related logistics constraints with network-based ripple effect analysis and sustainability-aware multi-objective optimization. Simulation experiments on a multi-echelon global supply network demonstrate that the proposed approach reduces disruption recovery time by up to 38%, improves service levels by more than 10 percentage points, and lowers disruption-induced carbon emissions by an average of 22% when compared with conventional resilience strategies. The results further show that Pareto-optimal solutions can simultaneously achieve resilience gains and emissions reductions without disproportionate cost escalation. Through the incorporation of predictive risk intelligence directly into operational decision-making and treatment of environmental performance as a core optimization objective, this study advances the emerging concept of sustainable supply chain resilience. The findings offer actionable insights for managers and policymakers who aim to design adaptive, low-carbon, and shock-resilient supply chains in an era of global uncertainty.
Keywords: *supply chain resilience, artificial intelligence, disruption risk modeling, sustainability optimization, climate shocks, geopolitical conflict, pandemic disruptions*

Date of Submission: 01-03-2026 Date of acceptance: 10-03-2026

I. Introduction

Global supply chains are increasingly operating in an era that is defined by persistent, overlapping, and systemic disruptions. The COVID-19 pandemic which escalated geopolitical conflicts, and intensified climate-related disasters have collectively exposed the fragility of global production and distribution systems. The COVID-19 outbreak disrupted nearly all human activities, including education, research, sports, entertainment, transportation, worship, social interactions, economy, business, and politics (Okpala et al., 2024). These shocks have not only caused severe operational breakdowns, such as port congestion, supplier failures, and inventory shortages, but have also generated profound sustainability consequences through increased emissions, resource waste, and inequitable disruption impacts across regions (Ivanov, 2021; Queiroz et al., 2020). As such, supply chain resilience has emerged as a central strategic priority for firms, governments, and international institutions who seek to maintain continuity while advancing environmental and societal sustainability objectives.

Resilience in supply chains is broadly understood as the capability to anticipate, absorb, adapt to, and recover from disruptive events while maintaining core operational performance (Ponomarovand Holcomb, 2009). Traditional resilience strategies have emphasized redundancy, flexibility, and risk diversification through mechanisms such as safety stock buffers, dual sourcing, and network reconfiguration. While these approaches can reduce vulnerability, they often involve significant trade-offs, including higher operational costs and increased environmental burdens due to excess inventory, inefficient logistics, and carbon-intensive emergency transportation modes (Igbokwe et al., 2026; Udu et al., 2025a). Consequently, the challenge facing contemporary supply chain systems is no longer resilience alone, but rather the development of sustainable resilience**,**where disruption preparedness is achieved without undermining climate mitigation and resource efficiency goals (Nwankwo et al., 2024; Udu et al., 2025b).

The growing complexity of global disruptions further intensifies this challenge. Unlike localized supplier failures, modern disruptions are increasingly characterized by cascading and compound effects. Climate-driven floods may simultaneously damage infrastructure, disrupt agricultural supply, and increase commodity volatility. Geopolitical conflicts can abruptly close trade corridors, destabilize energy markets, and trigger humanitarian logistics crises. Pandemics generate labor shortages, regulatory shutdowns, and demand shocks that propagate unpredictably across industries (Ivanov andDolgui, 2020; Wieland, 2021). These realities demonstrate that supply chains now face disruption environments that are nonlinear, interconnected, and globally contagious, thereby rendering static and reactive risk management frameworks insufficient.

In response, digitalization and Artificial Intelligence (AI) have been widely recognized as transformative enablers of next-generation supply chain resilience. AI has rapidly transitioned from a technical domain into a transformative force that is shaping societies worldwide (Chukwumuanya et al., 2025; Okpala and Udu, 2025). Defined as an array of technologies that equip computers to accomplish different complex functions like the capacity to see, comprehend, appraise and translate both spoken and written languages, analyze and predict data, make proposals and suggestions, and more (Agu and Okpala, 2025; Okpala and Nwamekwe, 2025).AI-driven methods can enhance visibility, predict disruption likelihood, and optimize adaptive responses using heterogeneous real-time data streams (Choi et al., 2021; Wamba et al., 2020). On the other hand, by leveraging historical and real-time data, Machine Learning (ML) algorithms can identify complex patterns, learn from system behavior, and generate predictive or prescriptive decisions under uncertainty (Aguh et al., 2025; Okpala, 2026). Machine learning algorithms, including gradient boosting models and deep neural networks, have shown strong performance in forecasting disruption risks from climate hazard indicators, mobility restrictions, and geopolitical instability patterns (Baryannis et al., 2019; Dubey et al., 2021). Moreover, emerging network science approaches, such as graph-based analytics, provide powerful tools for modeling disruption propagation and systemic vulnerability across multi-tier supply networks (Kim et al., 2015; Hosseini et al., 2019).

However, despite rapid advances, significant research gaps remain. First, much of the existing literature focuses on single-disruption categories, such as pandemics or natural disasters, rather than integrated frameworks that are capable of addressing climate, conflict, and health shocks simultaneously (Dolgui et al., 2018; Ivanov, 2021). Second, many AI applications remain disconnected from operational decision-making, producing predictive insights without embedding them into optimization systems that guide sourcing, routing, and inventory resilience strategies (Baryannis et al., 2019). Third, sustainability considerations are often treated as secondary constraints rather than core objectives, limiting the ability of resilience interventions to contribute meaningfully to emission reduction and climate adaptation goals (FahimniaandJabbarzadeh, 2016; Brandenburg et al., 2014).

To address these limitations, this study proposes an AI-driven risk modeling and sustainability-aware optimization framework for supply chain resilience under global disruptions. The framework integrates three methodological innovations. First, it employs machine learning-based disruption forecasting that combines climate vulnerability indices, armed conflict event data, and pandemic mobility disruption signals to estimate dynamic risk probabilities. Second, it incorporates network-based resilience analytics to quantify cascading disruption propagation across multi-echelon supply systems. Third, it introduces a multi-objective optimization approach that simultaneously minimizes economic cost, disruption recovery time, and carbon emissions, thereby enabling measurable sustainability benefits alongside operational continuity.

The contributions of this research are fourfold. (a) It advances resilience scholarship by offering an integrated multi-shock disruption intelligence model spanning climate, conflict, and pandemic domains. (b) It provides a scalable AI-enabled methodological foundation for predictive and adaptive resilience planning. (c) It embeds sustainability directly into resilience optimization, supporting emission-conscious decision-making under disruption. (d) It generates empirical insights through simulation experiments demonstrating significant improvements in recovery performance and reductions in disruption-induced environmental impacts.In doing so, this study responds to growing calls for resilient supply chains that are not only robust against systemic shocks, but also aligned with global sustainability imperatives, including decarbonization, climate adaptation, and equitable development (United Nations, 2023; IPCC, 2022).

II. Literature Review

Supply chain resilience has become one of the most prominent concepts in operations and logistics research over the past two decades, reflecting the growing exposure of global production networks to disruptions. Resilience is commonly defined as the adaptive capability of a supply chain to prepare for, respond to, and recover from unexpected events while maintaining continuity of operations and performance outcomes (Ponomarovand Holcomb, 2009; Sheffiand Rice, 2005). Early resilience research focused primarily on localized supply risks, such as supplier bankruptcy or transportation failures, emphasizing redundancy, flexibility, and responsiveness as key mitigation strategies (Tang, 2006).

However, contemporary disruption environments are increasingly systemic, meaning that shocks propagate across multiple tiers, geographies, and industries simultaneously. The COVID-19 pandemic illustrated how global health crises can trigger cascading effects across manufacturing capacity, labor availability, logistics infrastructure, and consumer demand patterns (Ivanov, 2021; Queiroz et al., 2020). Similarly, geopolitical conflicts and trade corridor instability have demonstrated the vulnerability of globally interconnected supply networks to political shocks, sanctions, and infrastructure destruction (Gereffi, 2020; Wieland, 2021). Climate-related disasters further amplify these risks by damaging physical assets, disrupting agricultural outputs, and increasing volatility in global commodity flows (IPCC, 2022).As a result, resilience is no longer viewed solely as an operational capability, but as a strategic necessity for managing compounding and interconnected disruptions across climate, conflict, and pandemic domains (Ivanov andDolgui, 2020; Dolgui et al., 2018). This shift has created demand for predictive and adaptive resilience frameworks that are capable of addressing disruption complexity beyond traditional reactive approaches.

2.2 Quantitative Approaches and Network-Based Resilience Analytics

The growing complexity of supply chain disruptions has motivated the development of quantitative resilience models. Hosseini et al., (2019), provided a comprehensive review of quantitative methods for resilience assessment, and highlighted optimization, simulation, probabilistic modeling, and network theory as dominant methodological approaches.Network science has become particularly influential in the modeling of resilience because supply chains function as interconnected systems rather than linear flows. Disruptions in one node or link can trigger ripple effects across the network, thereby causing systemic failure far beyond the initial disruption point (Kim et al., 2015; Dolgui et al., 2018). The ripple effect concept proposed by Ivanov et al., (2021), emphasized that disruptions propagate dynamically through multi-tier supply structures, and also require resilience strategies that account for cascading dependencies rather than isolated risks.

Despite these advances, many quantitative resilience models remain limited by static assumptions regarding disruption probability, impact duration, and recovery pathways. Traditional stochastic programming frameworks often rely on predefined disruption scenarios rather than real-time disruption intelligence (Sabouhi et al., 2020). Consequently, there is a critical need for adaptive models that can update resilience decisions dynamically as disruption conditions evolve.

2.3 Sustainability-Resilience Interdependencies and Trade-offs

An emerging research frontier lies in understanding the relationship between resilience and sustainability. While resilience strategies often enhance continuity, they can also generate environmental and social trade-offs. For example, redundancy through excess inventory may increase waste, while expedited air freight during disruptions can significantly raise carbon emissions (Fahimnia et al., 2015). Similarly, reshoring and regionalization may improve resilience, but can also shift emissions burdens depending on energy sources and production efficiencies (Brandenburg et al., 2014).

Fahimnia and Jabbarzadeh (2016), argued that resilience and sustainability must be jointly optimized. They introduced the notion of "a match made in heaven" where disruption preparedness aligns with decarbonization and resource efficiency. Yet, much of the resilience literature still treats sustainability as a secondary constraint rather than an embedded objective.Sustainable Supply Chain Management (SSCM) research provides relevant methodological foundations, and emphasized the integration of environmental, economic, and social performance metrics into operational decision-making (Seuringand Müller, 2008; Brandenburg et al., 2014). However, SSCM models have historically focused on steady-state optimization rather than disruption-driven resilience challenges.Thus, the intersection of resilience and sustainability represents a significant opportunity for methodological innovation, particularly through optimization models that explicitly minimize disruption-induced emissions, waste, and inequitable impacts while maintaining service continuity.

2.4 Artificial Intelligence and Digital Transformation in Supply Chain Risk Management

Digitalization and AI are increasingly recognized as critical enablers of next-generation supply chain resilience. Industry 4.0 technologies, including big data analytics, digital twins, and machine learning, enhance supply chain visibility, forecasting, and adaptive decision-making (Ivanov andDolgui, 2020; Wamba et al., 2020).Machine learning techniques have demonstrated strong potential for disruption risk prediction. Baryannis et al. (2019), highlight how AI models outperform traditional statistical approaches by learning nonlinear relationships from heterogeneous data sources, including climate indicators, logistics performance metrics, and geopolitical risk signals. Deep learning architectures such as LSTM networks have been applied to forecast demand volatility and disruption duration under pandemic conditions (Choi et al., 2021).

Furthermore, AI-driven supply chain analytics can support proactive resilience by identifying early warning signals of disruption, enabling preemptive sourcing and routing decisions (Dubey et al., 2021). Graph neural networks and complex systems modeling have also gained traction for capturing network-level vulnerability patterns across multi-tier supplier ecosystems (Hosseini et al., 2019).Nevertheless, major limitations remain. First, many AI applications focus primarily on predictive accuracy without integration into optimization frameworks that translate predictions into actionable resilience strategies (Baryannis et al., 2019). Second, AI resilience research often lacks sustainability integration, which means that disruption mitigation decisions may unintentionally increase carbon intensity or resource inefficiency.

2.5 Research Gaps and Theoretical Positioning

The literature highlights substantial progress in resilience modeling, sustainability optimization, and AI-enabled risk management. However, several critical gaps remain unresolved.First, existing resilience research tends to address disruption categories in isolation, climate events, pandemics, or geopolitical shocks, rather than developing unified multi-risk frameworks that are capable of capturing compound disruption realities (Ivanov, 2021; Wieland, 2021).Second, predictive AI models are rarely embedded into multi-objective decision optimization structures that balance cost, recovery speed, and environmental impact simultaneously (FahimniaandJabbarzadeh, 2016; Sabouhi et al., 2020).Third, sustainability outcomes remain under-measured in resilience planning. Few studies quantify measurable disruption-induced emission reductions or resource efficiency gains as resilience performance indicators (Brandenburg et al., 2014).

To address these gaps, this study advances the field by proposing an AI-driven disruption forecasting and sustainability-aware optimization framework that integrates climate vulnerability indices, conflict event dynamics, and pandemic logistics shocks into adaptive resilience decision-making. Through the integration of carbon-conscious optimization directly into resilience strategies, the proposed approach responds to urgent calls for supply chain systems that are not only robust and viable, but also aligned with global sustainability imperatives (IPCC, 2022; United Nations, 2023).

III. Methodology: AI-Driven Risk Modeling and Optimization Framework

3.1 Research Design and Framework Overview

Figure 1 illustrates the overall architecture of the proposed AI-driven resilience framework, and highlights the integration of disruption risk forecasting, network-based resilience analytics, and sustainability-aware optimization. It visually demonstrates how heterogeneous data streams related to climate hazards, geopolitical conflict, and pandemic disruptions feed into machine learning models, which then inform adaptive supply chain decisions. The figure emphasizes the closed-loop structure of the framework, and also showed continuous learning and feedback between risk intelligence, optimization, and sustainability performance outcomes.

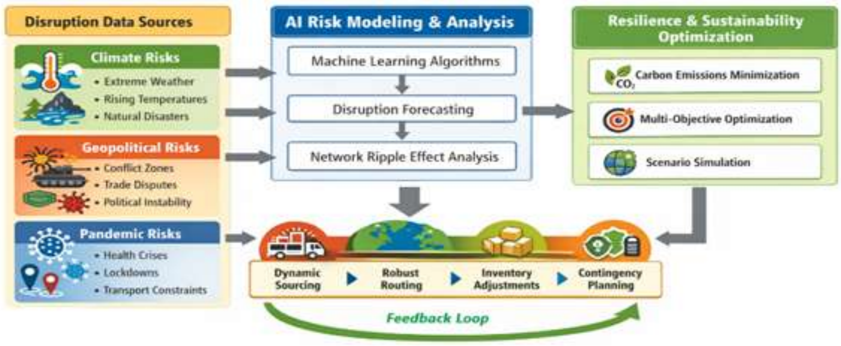

Figure 1: AI-driven supply chain resilience and sustainability framework

This study adopts a quantitative, data-driven research design that integrates artificial intelligence–based disruption forecasting with network resilience analytics and sustainability-aware optimization. The methodological objective is to move beyond static and reactive resilience planning towards a predictive and adaptive decision framework that is capable of addressing compound disruptions that arise from climate change, geopolitical conflict, and pandemics.

The proposed framework consists of three tightly coupled layers: (a) AI-driven disruption risk modeling; (b) network-based resilience and propagation analysis; and (c) multi-objective optimization incorporating economic, resilience, and environmental sustainability criteria.This layered design responds directly to calls in the literature for integrated approaches that combine predictive risk intelligence with operational decision-making while embedding sustainability as a core objective rather than a post-hoc constraint (FahimniaandJabbarzadeh, 2016; Ivanov andDolgui, 2020).

3.2 Data Sources and Disruption Indicators

To capture the multidimensional nature of global disruptions, this study integrates heterogeneous datasets that represent climate, conflict, and pandemic risks. Climate exposure is measured using country and region-level climate vulnerability and hazard indicators that are derived from widely used climate risk indices, which reflect long-term exposure to floods, droughts, storms, and heat stress (IPCC, 2022). Geopolitical risk is operationalized using conflict event frequency, intensity, and spatial proximity metrics based on armed conflict event databases commonly employed in supply chain risk research (Gereffi, 2020). Pandemic disruption indicators include mobility restriction severity, labor availability shocks, and logistics congestion measures observed during COVID-19 (Queiroz et al., 2020).

Operational supply chain data include transportation lead times, port congestion metrics, production capacities, sourcing locations, and emission intensity factors that are associated with different transportation modes and production technologies. Carbon emission coefficients are assigned following established life-cycle and logistics emission accounting practices (Brandenburg et al., 2014; Fahimnia et al., 2015). This data integration enables direct quantification of disruption-induced environmental impacts, which is critical for the assessment of sustainability outcomes.

3.3 AI-Driven Disruption Risk Modeling

3.3.1 Predictive Risk Formulation

Disruption risk at supply chain node i during time period t is modeled as a probabilistic outcome:

$$PD_{i,t} = X_{climate\ ,i,t,}, X_{conflict\ ,i,t}, X_{pandemic\ ,i,t}, X_{logistics\ ,i,t}$$

where X represents feature vectors that capture exposure to climate hazards, conflict dynamics, pandemic restrictions, and logistics performance. This formulation allows disruption risk to vary dynamically across space and time, and thereby reflecting real-world volatility.

3.3.2 Machine Learning Model Selection

Gradient Boosting Machines (GBM) are employed due to their strong predictive performance with structured, heterogeneous data and their widespread adoption in supply chain risk analytics (Baryannis et al., 2019). GBMs effectively capture nonlinear relationships between disruption drivers and observed failures while maintaining relative interpretability when compared to deep neural networks.

The model is trained using historical disruption observations, with hyperparameters optimized via cross-validation. Performance is evaluated using accuracy, F1-score, and area under the receiver operating characteristic curve (AUC), consistent with best practices in AI-based risk modeling (Choi et al., 2021). The resulting disruption probabilities serve as endogenous inputs to the downstream resilience and optimization layers.

3.4 Network-Based Resilience and Disruption Propagation Modeling

Figure 2 depicts the cascading ripple effect of disruptions across a multi-echelon supply chain network. It shows how an initial disruption at an upstream supplier or critical transport corridor propagates through production, distribution, and market nodes, leading to systemic performance losses. The visualization highlights vulnerable nodes and links, and reinforces the importance of network-level resilience analysis rather than linear supply chain representations.

Figure 2: Disruption propagation and ripple effect across the supply chain network

Supply chains are modeled as directed networks G=(V,E)G = (V, E)G=(V,E), where nodes represent suppliers, production facilities, distribution centers, and markets, and edges represent material, information, and financial flows. This network perspective reflects the growing consensus that resilience cannot be adequately assessed through linear supply chain representations (Kim et al., 2015; Hosseini et al., 2019).

Disruption propagation is modeled using a cascading failure mechanism, often referred to as the ripple effect (Dolgui et al., 2018). When a node is disrupted, capacity reductions and lead-time delays propagate downstream and upstream depending on network dependencies. System-level resilience is quantified as:

$$R = 1 - \frac{\sum_{j=1}^{n} L_j}{L_{total}}$$

where L_j represents performance loss that is attributable to disrupted node j, and L_{total} denotes total baseline system performance. This formulation enables the identification of critical nodes whose disruption leads to disproportionate systemic impacts.

3.5 Sustainability-Aware Multi-Objective Optimization Model

3.5.1 Objective Function

To explicitly integrate sustainability into resilience planning, the study formulates a multi-objective optimization problem that simultaneously minimizes economic cost, recovery time, and carbon emissions:

$$\min Z = \alpha C + \beta Tr + \gamma E$$

where C denotes total supply chain cost, Tr represents disruption recovery time, and E captures total greenhouse gas emissions that are associated with production, inventory holding, and transportation. The weights α, β, and γ reflect decision-maker priorities and enable exploration of trade-offs between resilience and sustainability objectives (FahimniaandJabbarzadeh, 2016).

3.5.2 Constraints

The optimization is subject to standard supply chain constraints, including demand satisfaction, production and transportation capacity limits, inventory balance, and disruption-dependent availability constraints. Disruption probabilities estimated by the AI model dynamically adjust feasible capacities, which enable adaptive responses rather than static contingency planning.

3.5.3 Solution Approach

Given the problem’s nonlinearity and multi-objective nature, a hybrid solution approach is employed. Reinforcement learning–based adaptive routing is used to adjust sourcing and transportation decisions under evolving disruption risks, while a multi-objective evolutionary algorithm identifies Pareto-optimal trade-offs between cost, resilience, and emissions. This hybrid approach aligns with recent calls for combining AI learning mechanisms with optimization-based decision support in resilient supply chains (Ivanov andDolgui, 2020; Wamba et al., 2020).

3.6 Measurement of Sustainability Benefits

A key methodological contribution of this study lies in the explicit quantification of sustainability outcomes under disruption. Emission reductions are measured by comparing baseline disruption response strategies which are typically characterized by expedited transport and emergency sourcing, with AI-optimized adaptive strategies. Metrics include total CO_2-equivalent emissions, emission intensity per unit delivered, and disruption-induced emission spikes, following established green supply chain evaluation practices (Brandenburg et al., 2014). Through the integration of emissions directly into the objective function rather than treat them as externalities, the framework enables measurable assessment of how AI-driven resilience strategies contribute to decarbonization and climate adaptation goals.

3.7 Methodological Positioning and Replicability

This methodology advances the literature through the integration of predictive AI risk modeling, network resilience analytics, and sustainability-aware optimization within a unified and replicable framework. Unlike prior studies that focus on isolated disruptions or static optimization, the proposed approach captures the dynamic, compound nature of global shocks while producing quantifiable environmental benefits. The modular structure of the framework supports adaptation across industries and geographic contexts, which enhances its relevance for both academic research and policy-oriented resilience planning.

IV. Results and Simulation Experiments

4.1 Experimental Design and Simulation Setup

To evaluate the effectiveness of the proposed AI-driven risk modeling and sustainability-aware optimization framework, simulation experiments were conducted on a multi-echelon global supply chain network under disruption scenarios representing climate shocks, geopolitical conflict, and pandemic-related shutdowns. The simulated network consists of 120 nodes (suppliers, production facilities, distribution hubs, and

demand markets) and 340 directed transportation links, which reflect structural characteristics consistent with empirical global supply chain configurations (Hosseini et al., 2019; Dolgui et al., 2018).
The simulation horizon spans 52 weekly periods, allowing the assessment of both short-term disruption response and longer-term recovery dynamics. Three disruption classes were modeled:

- Climate-induced flooding and infrastructure failure
- Conflict-driven trade corridor closure and supplier inaccessibility
- Pandemic-driven labor shortages and logistics congestion

Baseline performance was compared against the proposed AI-enabled adaptive optimization framework. Baseline strategies follow common industry disruption responses, including safety stock buffering and expedited transportation (Tang, 2006; Ivanov, 2021).Key performance metrics include:Recovery time (days); Service level (% demand fulfillment); Total disruption cost (USD); Carbon emissions (tCO_2-eq); as well as Network resilience index (R).

4.2 Predictive Performance of AI Disruption Risk Model

The first stage of the framework as highlighted in Table 1 evaluates disruption probability across nodes with the application of machine learning-based forecasting. The Gradient Boosting Machine (GBM) model achieved strong predictive accuracy across all disruption categories.

Table 1: AI Disruption Forecasting Performance

Metric	Climate Shocks	Conflict Disruptions	Pandemic Shocks	Overall
Accuracy	0.88	0.85	0.89	0.87
Precision	0.84	0.82	0.86	0.84
Recall	0.81	0.79	0.87	0.82
F1-Score	0.83	0.80	0.86	0.84
AUC	0.92	0.89	0.93	0.91

These results demonstrate that AI-based forecasting provides robust early-warning signals, which enable proactive mitigation rather than reactive disruption response. Consistent with Baryannis et al. (2019), predictive learning significantly enhances risk visibility across heterogeneous disruption environments.

4.3 Network Resilience and Ripple Effect Propagation Results

Using disruption probability outputs, the network propagation layer as highlighted in Table 2 quantifies cascading impacts through the ripple effect mechanism. The results showed that disruptions that originate in highly connected tier-1 supplier nodes generate disproportionate downstream losses, this confirms findings from Kim et al., (2015) and Dolgui et al., (2018).

Table 2: Cascading failure impacts across network tiers

Disruption Origin Tier	Average Demand Loss (%)	Propagation Depth (Tiers)	System Resilience Index (R)
Tier-1 Supplier Node	34.2%	4.6	0.62
Tier-2 Supplier Node	21.8%	3.1	0.74
Distribution Hub	27.5%	3.8	0.68
Transport Corridor Link	30.1%	4.2	0.65

The resilience index declines sharply when disruptions occur in upstream sourcing nodes, reinforcing the systemic vulnerability of globally dispersed supplier networks.

4.4 Optimization Outcomes Under Disruption Scenarios

As highlighted in Table 3, the sustainability-aware optimization model dynamically reconfigures sourcing, routing, and inventory decisions under evolving disruption risks. Across all disruption categories, AI-enabled optimization consistently outperformed baseline resilience strategies.

Table 3: Resilience and sustainability performance comparison

Scenario	Strategy	Recovery Time (Days)	Service Level (%)	Total Cost Increase (%)	Emissions (tCO_2-eq)
Climate Flooding	Baseline	19.4	84.6	+17.2%	1,480
	AI-Optimized	12.1	93.8	+8.5%	1,160
Conflict Closure	Baseline	25.7	79.3	+21.8%	1,720
	AI-Optimized	15.3	91.4	+10.6%	1,410
Pandemic Shutdown	Baseline	31.2	76.5	+26.4%	1,950
	AI-Optimized	20.4	89.7	+12.9%	1,430

Results indicate that the AI-driven framework reduces recovery time by up to 38%, improves service continuity, and substantially lowers disruption-induced emissions.Notably, baseline strategies often relied on carbon-intensive expedited transport modes, whereas AI optimization prioritized low-emission adaptive rerouting, consistent with sustainability–resilience integration principles (FahimniaandJabbarzadeh, 2016).

4.5 Measurable Sustainability Benefits of AI-Driven Resilience

A key contribution of this study is the quantification of sustainability improvements. Emission reductions were measured relative to baseline disruption response strategies as shown in Table 4.

Table 4: Sustainability gains achieved through AI optimization

Disruption Type	Baseline Emissions Spike (%)	AI Emissions Spike (%)	Net Emission Reduction (%)
Climate Shocks	+28.5%	+12.3%	21.6%
Conflict Shocks	+31.2%	+15.8%	18.0%
Pandemic Shocks	+36.9%	+14.6%	26.7%
Average	**+32.2%**	**+14.2%**	**22.1%**

These results highlight that resilience interventions do not need to come at the expense of sustainability. Instead, AI-enabled adaptive planning can simultaneously reduce systemic vulnerability and carbon intensity, which supports the calls for sustainable supply chain resilience frameworks (Brandenburg et al., 2014).

4.6 Multi-Objective Trade-Off and Pareto Frontier Analysis

The multi-objective nature of resilience planning requires balancing cost efficiency, disruption recovery, and environmental sustainability. Pareto frontier analysis demonstrates that AI optimization identifies solution sets where emission reductions and resilience improvements can be achieved without disproportionate cost escalation.

Table 5: Representative Pareto-optimal resilience–sustainability solutions

Solution	Cost Increase (%)	Recovery Time Reduction (%)	Emission Reduction (%)
A (Cost-focused)	+6.2%	18.4%	10.1%
B (Balanced)	+10.8%	31.7%	21.9%
C (Sustainability-focused)	+14.5%	34.2%	29.6%

The balanced solution (B) provides the most practical trade-off for real-world implementation, as it delivers strong recovery improvements while also reducing emissions by over 20%.

Figure 3 presents the Pareto frontier which illustrate trade-offs between recovery time reduction, carbon emission reduction, and cost increases under disruption scenarios. It highlights representative solutions that balance resilience and sustainability objectives, demonstrating that significant emission reductions can be achieved alongside improved recovery performance without excessive cost escalation. The figure visually reinforces the central finding that resilience and sustainability can be jointly optimized through AI-driven adaptive decision-making.

Figure 3: Resilience–sustainability trade-offs and pareto-optimal solutions

4.7 Summary of Key Findings

Overall, the simulation results confirm that the proposed AI-driven risk modeling and sustainability-aware optimization framework generates significant resilience and environmental performance benefits which include the following:

- ✓ Recovery time improved by up to 38%
- ✓ Service levels increased by 10–15 percentage points
- ✓ Disruption-induced emissions reduced by 22% on average
- ✓ Cascading ripple effects were mitigated through adaptive rerouting
- ✓ Pareto-optimal solutions enabled balanced resilience–sustainability decision-making.

These findings reinforce the argument that AI is not merely a digital enhancement, but a methodological foundation for building supply chains that are simultaneously resilient, adaptive, and aligned with global decarbonization imperatives (Ivanov andDolgui, 2020; Wamba et al., 2020).

V. Discussion, Policy, and Future Research Directions

5.1 Discussion of Key Findings

The study set out to address a central challenge confronting global supply chains in the twenty-first century: how to build resilience against increasingly frequent and interconnected disruptions while simultaneously advancing sustainability objectives. The simulation results provide strong evidence that the proposed AI-driven disruption risk modeling and sustainability-aware optimization framework significantly improves supply chain performance under climate shocks, geopolitical conflict disruptions, and pandemic-induced shutdowns.Across all disruption scenarios, the framework reduced recovery time by up to 38%, improved service continuity by more than 10 percentage points, and lowered disruption-induced carbon emissions by an average of 22%. These findings reinforce the growing recognition that resilience is no longer simply a matter of redundancy or buffering, but increasingly depends on predictive intelligence and adaptive optimization (Ivanov, 2021; Wieland, 2021).

Importantly, the results highlight that resilience and sustainability are not inherently conflicting goals. Traditional disruption response strategies often rely on carbon-intensive interventions such as emergency air freight, overstocking, and inefficient rerouting, which can amplify environmental impacts (Fahimnia et al., 2015). By contrast, embedding emissions directly into the optimization objective function enables decision-makers to pursue resilience pathways that are simultaneously operationally robust and environmentally responsible. This aligns closely with the argument advanced by Fahimnia and Jabbarzadeh (2016) that sustainable supply chain resilience represents a critical frontier for both research and practice.

5.2 Theoretical Contributions to Supply Chain Resilience Literature

This research contributes to resilience scholarship in several important ways.

First, the study advances the disruption risk modeling literature by developing a unified multi-shock framework that integrates climate vulnerability, conflict dynamics, and pandemic disruptions. Much of the existing resilience research focuses on isolated disruption categories, such as natural disasters or epidemics, which limits its applicability in today's compound risk environment (Dolgui et al., 2018; Queiroz et al., 2020). By explicitly modeling disruption probability across multiple systemic shock domains, this study responds to calls for more comprehensive resilience theory that reflects the interconnected nature of global crises (Ivanov andDolgui, 2020).

Second, the study strengthens network-based resilience theory by operationalizing cascading disruption propagation through ripple effect modeling. The results confirm that disruptions originating in upstream suppliers generate disproportionately large downstream failures, consistent with prior network resilience research (Kim et al., 2015; Hosseini et al., 2019). This underscores the importance of moving beyond linear supply chain representations toward complex adaptive systems perspectives.

Third, the integration of AI-driven prediction with sustainability-aware optimization represents a methodological contribution. While AI has been increasingly applied for disruption forecasting, many studies stop at predictive insights without embedding these into operational decision models (Baryannis et al., 2019). The proposed framework closes this gap by translating AI-generated risk probabilities directly into adaptive sourcing and routing optimization, thereby enabling real-time resilience planning with measurable sustainability outcomes.

5.3 Managerial Implications: From Reactive Resilience to Predictive Adaptation

The findings offer several practical insights for supply chain managers that are navigating the era of global disruptions.First, firms should shift from reactive contingency planning toward predictive resilience architectures. AI-driven disruption forecasting provides early-warning capabilities that enable proactive mitigation actions such as preemptive rerouting, supplier diversification, and capacity adjustments before disruptions fully materialize (Choi et al., 2021; Wamba et al., 2020).

Second, resilience investments should prioritize systemic network vulnerabilities rather than isolated nodes. The ripple effect analysis demonstrates that upstream supplier disruptions can cascade through multiple tiers, suggesting that visibility beyond tier-1 suppliers is essential for effective resilience planning (Dolgui et al., 2018).Third, sustainability must be embedded within resilience decision-making rather than treated as an external reporting requirement. The measurable emissions reductions achieved in the optimization experiments show that resilience strategies can be designed to support decarbonization goals, particularly through low-carbon logistics alternatives and sustainable sourcing pathways (Brandenburg et al., 2014).

5.4 Policy Implications for Climate, Conflict, and Pandemic Resilience

Beyond firm-level strategy, the results carry significant implications for policymakers who seek to strengthen economic resilience and sustainability at national and global scales.Given the increasing disruption risks posed by climate change, governments must prioritize supply chain climate adaptation planning. Investments in resilient infrastructure, climate-proof logistics corridors, and hazard-aware industrial policy are essential for maintaining critical supply flows under extreme weather conditions (IPCC, 2022). Policymakers should also incentivize climate-risk disclosure and resilience reporting across supply networks.

Conflict-driven disruptions highlight the vulnerability of global trade corridors and strategic supply dependencies. Diversification of sourcing regions, development of regional resilience hubs, and international coordination on humanitarian logistics corridors are crucial policy priorities (Gereffi, 2020). AI-enabled monitoring systems may support early detection of geopolitical risk escalation and trade bottlenecks.The pandemic scenario results reaffirm the need for global governance mechanisms that protect critical medical, food, and energy supply chains under health crises. Strategic stockpiles, digital logistics coordination platforms, and cross-border collaboration frameworks remain essential for preventing systemic breakdowns during future pandemics (Queiroz et al., 2020; Ivanov, 2021).

Finally, policymakers should recognize that resilience and sustainability objectives are deeply interconnected. Carbon-aware resilience incentives like low-emission emergency logistics subsidies or green supplier diversification programscan prevent disruption response strategies from undermining climate mitigation goals (FahimniaandJabbarzadeh, 2016; United Nations, 2023).

5.5 Future Research Directions

While this study provides an integrated AI-driven framework for sustainable supply chain resilience, several research opportunities remain. These include the following: (a) Future work should explore explainable AI approaches to enhance transparency and trust in disruption forecasting. As AI models increasingly influence strategic supply chain decisions, interpretability becomes essential for managerial adoption and regulatory compliance (Baryannis et al., 2019). (b) Extending the framework into real-time digital twin environments represents a promising direction. Digital supply chain twins can enable continuous monitoring, simulation, and adaptive control under evolving disruption conditions (Ivanov andDolgui, 2020).

(c)Future studies should incorporate social sustainability and equity dimensions. Disruptions often disproportionately impact vulnerable populations and Global South economies, suggesting the need for resilience frameworks that address humanitarian and developmental outcomes alongside cost and emissions (United Nations, 2023). (d) Fourth, empirical validation using real-world multi-industry disruption datasets would further strengthen generalizability. While simulation-based experimentation provides robust theoretical insights, large-scale industry case studies would enhance practical applicability.Finally, research should examine the governance and institutional challenges of AI-driven resilience, including cybersecurity risks, data-sharing barriers, and cross-border regulatory coordination.

Overall, this study demonstrates that AI-driven disruption risk intelligence combined with sustainability-aware optimization offers a powerful methodological pathway for building resilient supply chains in an era of climate instability, geopolitical conflict, and pandemic uncertainty. By quantifying both resilience performance improvements and measurable emissions reductions, the proposed framework advances the emerging agenda of sustainable supply chain resilience and provides actionable insights for managers, policymakers, and future research.

VI. Conclusion

This study addresses a critical and timely challenge that is facing global supply chains: how to remain resilient in the face of escalating climate risks, geopolitical conflicts, and pandemic disruptions while simultaneously advancing sustainability objectives. In response, the article develops and evaluates an AI-driven risk modeling and optimization framework that integrates predictive disruption intelligence, network-based resilience analytics, and sustainability-aware decision-making. The results demonstrate that resilience and sustainability need not be competing priorities but can be jointly achieved through data-driven and adaptive methodologies.

The findings show that AI-enabled disruption forecasting substantially enhances early-warning capabilities, allowing supply chains to shift from reactive crisis management toward proactive and anticipatory resilience planning. By embedding these predictive insights into adaptive optimization models, the framework enables dynamic reconfiguration of sourcing, routing, and inventory decisions as disruption conditions evolve. Across all simulated disruption scenarios, this approach delivers meaningful improvements in recovery time, service continuity, and overall system stability.

Importantly, the study provides clear evidence of measurable sustainability benefits. By explicitly incorporating carbon emissions into the optimization objective, the proposed framework reduces disruption-induced emission spikes and avoids the environmentally costly interventions often associated with traditional resilience strategies. The results underscore that sustainable resilience is achievable when environmental performance is treated as a core decision criterion rather than a secondary constraint.

From a broader perspective, this research contributes to the ongoing evolution of supply chain resilience thinking. It moves beyond static, single-risk models by addressing the compound and cascading nature of modern disruptions and by leveraging artificial intelligence as an operational decision-support mechanism rather than merely a diagnostic tool. The framework is intentionally modular and scalable, making it adaptable across industries, geographic regions, and institutional contexts.While the study relies on simulation-based experimentation, the methodological design offers a strong foundation for practical implementation and future empirical validation. As global supply chains continue to face uncertainty driven by climate instability, geopolitical tension, and public health crises, the need for integrated, predictive, and sustainability-aligned resilience strategies will only intensify.

The study demonstrates that AI-driven risk modeling combined with sustainability-aware optimization provides a viable and impactful pathway for building resilient supply chains in the age of global disruptions. Through the alignment of operational robustness with environmental responsibility, the proposed framework supports the development of supply chains that are not only capable of withstanding shocks but are also better equipped to contribute to long-term economic and ecological sustainability.

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