

# Artificial Intelligence and Supply Chain Resilience: A Three-Stage Framework for Prediction, Response, and Adaptive Learning

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## Abstract:

Heightened exposure of global supply chains to systemic shocks (e.g., geopolitical tensions and climate-related disruptions). These “black swan” events keep repeating, highlighting the urgent need for more resilience to keep operations going. The improvement of the resilience of the supply chain has become an important method for logistics enterprises, including manufacturing and circulation enterprises, to resist operational risks and maintain long-term stable operation. Although existing literature recognises the potential of AI in various individual supply chain functions, there is a notable lack of systematic integration of AI in the canonical three-stage resilience framework of prediction, response, and recovery/learning. Moreover, practical constraints such as data scarcity and algorithmic opacity are generally ignored. This paper uses the method of systematic literature review, integrates and sorts out the relevant cutting-edge research results at home and abroad, analyses the differentiated empowerment paths of artificial intelligence in each stage of supply chain resilience at different levels, proposes supporting optimisation solutions for various technical limitations and fills in the gap of phased integrated research in the current field. This research contributes to the discourse on digital resilience by reconciling the transformative potential of AI with its inherent limitations. The framework offers actionable insights for managers who seek to balance algorithmic efficiency and human oversight and ethical governance in volatile global markets.

**Keywords:** Supply Chain Resilience; Artificial Intelligence; Explainable AI (XAI); Risk Management; Digital Transformation

## 1. Introduction

### 1.1 The Evolving Landscape of Supply Chain Vulnerability

Global supply chains are currently in the process of transitioning from linear, efficiency-oriented networks to complex, interconnected ecosystems that are susceptible to systemic shocks. This evolution has revealed weaknesses that threaten macroeconomic stability. The supply chain is a link connecting various stages of production, distribution and circulation, and is also a key point to ensure the smooth operation of economic cycles. The recent rise of geopolitical tensions and climate disruptions has demonstrated that traditional risk mitigation methods are no longer sufficient. As a result, AI has become a crucial technological front-runner, providing new possibilities for adaptive management and predictive analytics. However, the integration of AI in resilience building is nascent and fragmented. This paper takes the academic literature published on the cross-theme of “Artificial Intelligence” and “Supply Chain Resilience” as the research object. This section describes the impact of AI on supply chain resilience and its underlying mechanisms, as well as its potential drawbacks, through a comprehensive summary and organisation of the previous literature.

### 1.2 Theoretical Underpinnings and Research Gaps

The conceptualisation of Supply Chain Resilience (SCR) has evolved over the past two decades. Christopher and Peck’s seminal work defined resilience as the ability to return to an optimal state after disruption [1]. Later, Ponomarov and Holcomb developed this perspective, describing resilience not as a fixed characteristic but as a multi-stage, dynamic adaptive process [2]. In this tripartite framework, AI applications have demonstrated significant potential. Modgil et al. have demonstrated the effectiveness of AI in early warning of risk and emergency response, but also pointed out the limitations of AI in terms of adaptability to scenarios [3]. Likewise, Xu et al. have shown that AI can mitigate information asymmetry and the bullwhip effect by scheduling optimisation [4]. Data dependency and algorithmic opacity are two systemic constraints that hinder real-world implementation, but these studies mainly focus on algorithmic efficacy alone.

The two major research directions, namely the stage division of supply chain resilience and the risk management and control of AI, have been discussed in depth in the existing literature. But there is obviously a disconnect between these two lines of research. However, most of the literature on AI-enabled supply chains focuses on discussing the technical advantages, such as prediction,

early warning and emergency scheduling, and the value of the algorithms in cost reduction, efficiency improvement and mitigating the bullwhip effect. Few studies have dealt with the multiple constraints of implementing such a technology, and a systematic categorisation is still lacking. In contrast, relevant studies based on the three-stage resilience framework mainly pay attention to the analysis of traditional resilience approaches, such as human resources, inventory and supplier redundancy, and do not carry out a complete and deep phased mechanism dissection of AI-based digital tools. At the same time, only a very few scholars are considering the pros and cons of the application of AI technology. No integrated analytical logic has been built and proposed for the entire process of prediction, response, recovery and learning, and no corresponding multi-dimensional implementation optimisation schemes covering technology, organisation and risk have been built and proposed. The present paper intends to fill this major gap in research.

### 1.3 Conceptual Framework and Methodological Approach

Phase 1: Theoretical Foundation and Gap Analysis. The paper starts with a systematic literature review (SLR) of seminal works on SCR and AI-enabled risk management. This stage is a dialectical synthesis of existing achievements and limitations for defining the research boundary and identifying a specific niche of this paper.

Phase 2: Mechanism Dissection. This paper studies the heterogeneous AI empowerment pathways in line with the canonical three-stage resilience model (Prediction, Response, Recovery/Learning). This includes further discussion on how AI increases situational awareness, enables dynamic decision making and promotes adaptive learning to improve the anti-disturbance ability of supply chains.

Phase 3: Framework Development & optimisation This paper synthesises key constraints in data integrity, algorithmic transparency and organisational readiness, drawing from digital transformation practices. In this regard, this paper advocates an integrated optimisation framework based on three pillars: technological governance, organisational collaboration, and risk management.

### 1.4 Dialogue with Existing Literature

Supply chain resilience and artificial intelligence are two research streams that are largely pursued in parallel, creating prominent theoretical gaps that this paper seeks to fill. The classic resilience scholars Christopher and Peck (2004) and Ponomarov and Holcomb (2009) developed the three-stage dynamic resilience framework around disruption prediction, emergency response and post-event recovery, but they only discussed traditional physical mitigation tactics, not digital intelligent enablers like AI.

Recently, Modgil et al. (2022) and Xu et al. (2025) have validated the strengths of AI in demand forecasting, information symmetry improvement and bullwhip effect suppression across scattered supply chain links, but they do not systematically match AI functions to the complete three-stage resilience cycle and tend to overlook pervasive practical constraints including heavy data reliance. Existing reviews are mainly presented separately with resilience strategies and AI logistics applications, without integrated analytical logic for the whole risk management process, and without proposed targeted multi-dimensional optimisation schemes covering technology, organisation and risk governance to address the inherent limitations of AI. In this regard, this research incorporates differentiated AI empowerment paths into the canonical three-stage resilience framework, balances the discussions on the technical merits and practical drawbacks of intelligent algorithms, and builds a complete closed-loop analytical

system to remedy the above research deficiencies.

## 2. Theoretical Evolution of Supply Chain Resilience and AI Integration

The conceptualisation of Supply Chain Resilience (SCR) has undergone a paradigm shift from static recovery capabilities to dynamic adaptive processes [1,5]. This progressive redefinition enriches the connotation of anti-interference capacity for global supply networks, but the chronological evolution of resilience theories summarised by previous researchers seldom incorporates digital transformation factors and ignores the reshaping effect brought by AI technology to each resilience link. Table 1 chronicles this theoretical evolution, highlighting the seminal contributions that underpin the three-stage framework adopted in this study [3,6].

**Table 1. Evolution of SCR Definitions and AI Integration**

| Phase/ Period             | Core Concept         | AI Integration Logic                        |
|---------------------------|----------------------|---------------------------------------------|
| Foundational (Pre-2004)   | Recovery & Stability | Automation & Descriptive Analytics          |
| Developmental (Post-2004) | Dynamic Adaptation   | Predictive Analytics & Decision Support     |
| Contemporary (Post-2020)  | Bullwhip Suppression | Autonomous optimisation & Adaptive Learning |

As shown in Table 1, each developmental stage of the theory of supply chain resilience is restricted by certain types of intelligent technology integration. In the foundational stage, research only used basic descriptive analysis tools and could not proactively predict risks. In the developmental stage, scholars introduced predictive analytics, but only applied algorithmic tools to single operational segments rather than the entire resilience cycle. In the contemporary post-pandemic stage, research has recognized the autonomous adaptive learning capabilities of AI, but still lacks systematic alignment between autonomous optimisation and multi-stage dynamic resilience requirements. The following chapters of this paper address the core theoretical shortcoming of the missing linkage between the three-stage resilience model and full-process AI application. After the COVID-19 pandemic, the vulnerability of supply chains has been exposed, and countries and enterprises have begun to seek tools to enhance SCR [3]. In this context, as an emerging technology, AI has been applied to this field. It has improved the capabilities of supply chains in demand forecasting, risk management, inventory optimisation, and other aspects, and enhanced logistics efficiency and corporate decision-making efficiency [7]. Smart algorithms are developing at a fast pace, but the existing AI solutions are still immature for real-world supply chain scenarios. There are still several intrinsic limitations, e.g., poor controllability of the system, unsolved

algorithmic ethical hazards, etc. Therefore, researchers and practitioners should provide a balanced assessment of the empowering values and hidden drawbacks of AI for strengthening SCR.

## 3. AI-Driven Mechanisms Within the Three-Stage Resilience Framework

In academic literature, SCR is commonly defined as “the ability of a supply chain to respond quickly to a series of unforeseen and sudden disruptive events and recover to its original level, while learning and adapting to achieve a superior operational level” [1,2,8]. This definition moves beyond the static early perspective that was only based on “recovery” and points to the importance of the dynamic capabilities such as “adaptation” and “learning”. From this, the construction of SCR is often divided into three progressive phases: Predictive, Responsive, and Recovery & Learning [2]. Although investments are increasing, there is still only a rudimentary understanding of the micro-mechanisms of how AI is working across these different stages. This section fills this gap by providing an explicit description of the specific algorithmic interventions at each stage. This paper will describe the impact of AI on SCR in these three phases.

### 3.1 Prediction Stage: Situational Awareness and

## Risk Anticipation

### 3.1.1 Mitigating uncertainty via multi-dimensional data fusion

Traditional prediction models often rely on historical sales data, which makes them ill-suited to respond to “black swan” events. That is, small-probability events that are hard to predict in advance but will have a huge impact once they happen. The most important benefit of AI is its ability to predict demand and supply even in the presence of uncertainty and imperfect information [7]. It can handle various types of multi-dimensional information, such as macroeconomic indicators, public sentiment on social media, user search trends, etc., to greatly improve the accuracy of demand prediction. AI also ingests weather data, real-time port congestion data and geopolitical news 24/7 to track covert supply chain threats and generate early risk alerts when raw material shortages or transportation disruptions arise.

### 3.1.2 Deduction of cascading risk pathways via NLP

The AI system is capable of performing natural language processing (NLP) on unstructured data such as unrest in local areas, natural disaster threats or policy changes [9]. AI cannot only identify the single risk point, but also can deduce the transmission path of the risk in the supply chain network by establishing an association rule model [9]. For example, AI is able to assess the impact of a strike event quickly in a certain region on the delivery of downstream multi-tier suppliers, and generate an early warning report in a short period of time to inform companies in the upstream and downstream, thus providing a critical buffer period to deal with the impact and reduce losses.

## 3.2 Response Stage: Information Transparency and Dynamic Decision-Making

### 3.2.1 Blockchain-AI integration for information symmetry

The “bullwhip effect” is due to the information asymmetry at different stages of the supply chain. AI-powered supply chain control towers break down information silos, broaden communication reach and speed up the dissemination of information across the network [4]. The combination of AI and blockchain technology can share information on inventory levels, order statuses and in-transit logistics among upstream and downstream enterprises in real time, ensuring transparency of supply and demand information, and effectively curbing chain reactions induced by pan-

ic-driven stockpiling or excessive production cuts.

### 3.2.2 Computational augmentation for multi-objective optimisation

People’s responses to exogenous shocks are often constrained by cognitive load and processing speed. Artificial intelligence has strong computing power and can perform data analysis in complex and changing environments at the millisecond level. For instance, when unexpected logistics bottlenecks occur, AI algorithms can swiftly start dynamic demand forecasting, adaptive inventory adjustment, search for alternate transportation schemes, and dynamic planning for the vehicle routing problem (VRP) [1,2,10]. The anti-interference capability of the supply chain could be improved if the algorithms could adopt a more efficient calculation of the optimal solution of Pareto than the traditional manual decision-making to balance the cost, timeliness and risk.

## 3.3 Recovery & Learning Stage: Closed-Loop optimisation and Adaptive Evolution

### 3.3.1 Retrospective diagnostics and bottleneck resolution

During the physical recovery process, AI tools can incorporate real-time data from different links being monitored during emergencies, for example, equipment failure rate, personnel on-duty rate, and material completeness rate. AI is able to identify supply chain bottlenecks [4] by comparing actual performance against preset indicators. This allows AI to specifically optimise enterprise production scheduling and MRP, thus reducing the recovery cycle.

### 3.3.2 Continuous model evolution through reinforcement learning

Learning is an expression of the advanced form of SCR [11]. AI is capable of self-evolution, by using the features of current disruptions, response measures and final results as a new training dataset and feeding them into the existing prediction model. For enterprises, deep learning enables AI to adapt the model’s parameters to fit the new normal of market changes, one step at a time [11]. This continuous iteration of the model reduces the potential losses caused by similar uncertain events in the future, and realises the upward spiral improvement of the supply chain operation level. The recursive logic of predictive analytics, responsive execution, and adaptive learning constitutes the core of the AI-augmented resilience framework, summarised in Table 2.

**Table 2. Logical Structure of AI Empowering Supply Chain Resilience Based on Three-Stage Resilience Framework**

| Layer                                                                | Category / Stage             | Items / Functions                                                                                                                      | Logical Relationship                                                                                                                                                                    |
|----------------------------------------------------------------------|------------------------------|----------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Layer 1: Sources of External Disruptions                             | Disruption Types             | (1) Geopolitical Conflicts;<br>(2) Natural Disasters;<br>(3) Supply-demand Fluctuations;<br>(4) Policy Changes;<br>(5) Port Congestion | Input to Layer 2: These external disruptions trigger the need for supply chain resilience processes.                                                                                    |
| Layer 2: Three Core Stages of Supply Chain Resilience                | 1. Prediction Stage          | (1) Eliminate supply and demand uncertainties;<br>(2) Visualise risk transmission paths                                                | Response to Layer 1: These stages represent the procedural mechanism to cope with the disruptions identified in Layer 1.                                                                |
|                                                                      | 2. Response Stage            | (1) Break information silos;<br>(2) Alleviate the bullwhip effect;<br>(3) Support real-time emergency decision-making                  |                                                                                                                                                                                         |
|                                                                      | 3. Recovery & Learning Stage | (1) Repair supply chain weak links;<br>(2) Realise adaptive model evolution                                                            |                                                                                                                                                                                         |
| Layer 3: Restricting Factors & Corresponding optimisation Dimensions | Restricting Factors          | (1) Data defects;<br>(2) Unexplainable algorithms;<br>(3) Shortage of organisational talents;<br>(4) Ethical compliance risks          | Constraint on Layers 1 & 2: These factors limit the effectiveness of the resilience stages (Layer 2) in mitigating the disruptions (Layer 1), defining the boundaries for optimisation. |

## 4. Governance Framework for AI-Augmented Supply Chain Resilience

Based on the three-stage framework of SCR, namely prediction, response, and recovery, this paper systematically sorts out the positive roles of AI in improving situational awareness, decision-making efficiency, and adaptive learning capability. However, the application of AI is not without flaws. Data quality dependence, the “black box” characteristic of algorithms, and ethical and compliance issues remain the key factors restricting the exertion of its effectiveness [11]. To further unlock the potential of AI in building SCR, optimisation should be carried out from three dimensions, including technological governance, organisational collaboration and risk control.

### 4.1 Technical Governance: Data Integrity and Algorithmic Explainability

#### 4.1.1 Establishing inter-organisational data governance

It is proposed that enterprises should take the lead in establishing an inter-organisational data governance system and formulate unified data interface standards and exchange protocols. Cleaning the historical data, removing outliers and imputing missing data can improve the quality of the training data set. In the meantime, Internet of

Things (IoT) devices should be implemented to improve real-time performance and data granularity, guaranteeing that AI models receive accurate inputs and minimising the risk of “Garbage in Garbage Out” (GIGO) from the start [11].

#### 4.1.2 Implementing explainable AI (XAI) for trustworthy decision-making

To tackle the ‘black box’ issue of AI decision making, it is suggested to apply explainable artificial intelligence (XAI) techniques at critical decision-making points in the supply chain, like credit approval and supply disruption determination [12]. XAI can give reasoning to explain decisions, allowing managers to know not only “what decision the AI made” but also “why it made that decision.” This improves the reliability of human-machine collaboration and makes it easier to trace responsibility and fix models when AI decisions are wrong [12].

### 4.2 organisational Synergy: Human-AI Hybrid Intelligence

#### 4.2.1 Institutionalising Human-in-the-Loop (HITL) oversight

Deep reliance on AI in the recovery and learning stage of supply chain resilience management is precarious. It is recommended to establish a decision-making mechanism

of “human-in-the-loop”, in which AI is responsible for processing massive data and generating preliminary solutions, and human experts are responsible for making final decisions and intervening in abnormal situations [12]. The hybrid enhanced intelligence model can take advantage of the computational capabilities of AI and still keep the human intuition in the value judgement, creative thinking, and crisis management [11].

#### **4.2.2 Cultivating hybrid competencies and inclusive incentives**

In response to the demands of the AI era, enterprises should strengthen digital skill training for existing employees and cultivate interdisciplinary talents who master both supply chain management processes and basic AI knowledge. In addition, companies should also adjust the performance appraisal system to encourage employees to actively use AI tools to assist decision-making, rather than resisting technological change, so as to eliminate the phenomenon of “technology rejection” within the organisation [11].

### **4.3 Risk Mitigation: Ethical Boundaries and Redundant Safeguards**

#### **4.3.1 Defining ethical guardrails and privacy-preserving protocols**

Corporations should collaborate with industry associations to formulate ethical guidelines for the application of AI in the supply chain domain. Explicit prohibitions shall be established against the use of AI for price collusion, data monopoly, or unfair transactions. Enterprises should strictly abide by the relevant laws and regulations in data privacy protection, use privacy-preserving computing technologies such as federated learning to achieve joint modelling without transferring raw data, and balance the relationship between data sharing and privacy protection [12].

#### **4.3.2 Maintaining strategic physical redundancy as a fail-safe**

Excessive reliance on AI-powered, precise predictions may lead enterprises to reduce traditional safety stocks or reserve capacities. However, in extreme scenarios such as algorithm failure, data contamination, or cyberattacks, physical redundancy remains the final line of defence. Therefore, under the promotion of AI-enabled lean management, it is recommended that enterprises keep appropriate buffer stocks or multi-supply channels according to the results of risk assessments, and establish a dual guarantee system of “digital intelligence + physical redundancy” to prevent systemic collapse [11].

## **5. Conclusion**

### **5.1 Core Findings**

This paper focuses on the three-stage model of SCR: prediction, response and recovery, and systematically analyses the impact and mechanism of AI on supply chains at each stage. The study identifies three closely linked channels through which artificial intelligence gradually enhances the adaptiveness of supply chains in volatile market environments: proactive risk alerting, rapid emergency response and continuous model iteration. In practice, intelligent tools reduce uncertainty in supply and demand, facilitate the exchange of information between supply chain partners and increase the precision of production planning. However, deploying AI is hampered by several constraints, such as heavy reliance on high-quality input data, opaque algorithmic logic, poor internal organisational fit, and systemic risks arising from over-reliance on digital systems.

### **5.2 Research Significance**

The purpose of this study is to help businesses in the supply chain use AI in a consistent way, so they can lessen the effects of outside forces disrupting their supply chains (such as wars or natural disasters) and cut down on losses caused by unforeseen circumstances. Moreover, the proposed AI ethics and privacy protection framework serves as a reference for digital regulation in the industry, promoting the development of supply chain digitalisation towards security, fairness, and sustainability, thus alleviating the macroeconomic negative effects of global supply chain instability.

### **5.3 Limitations and Future Research Directions**

This study mainly uses secondary literature for theoretical review, without first-hand enterprise research data and empirical support from practical operation perspectives. It also does not differentiate the digitalisation differences between the industries and sizes of enterprises, which leads to a limited targeted analysis. Also, the research does not demonstrate the significant effect of AI on SCR by quantitative models.

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