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AI-Driven Self-Healing Supply Chains and the Future of Logistics Automation

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ABSTRACT

This study examines how artificial intelligence (AI) enables self-healing capabilities in global supply chains and reshapes logistics automation. Employing a qualitative multi-case study design, data were collected through 42 semi-structured interviews across six multinational organisations in manufacturing, retail, and third-party logistics. Thematic analysis yielded four themes: AI-enabled disruption sensing; autonomous reconfiguration mechanisms; human-AI collaboration and workforce transformation; and ethical and governance considerations. Findings demonstrate that self-healing capability emerges from the dynamic interplay between AI infrastructure, adaptive organisational routines, and human agency - not from technology alone. Organisations embedding AI within a dynamic capabilities' framework achieve measurable reductions in disruption recovery time and operational costs. A grounded theoretical model of AI-driven supply chain self-healing is proposed, integrating dynamic capabilities theory and complex adaptive systems theory. Practical implications for supply chain leaders and directions for future mixed-methods research are discussed.

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Introduction

The global supply chain landscape has undergone unprecedented stress in recent years, with cascading disruptions arising from geopolitical tensions, pandemic-induced demand volatility, climate-related extreme weather events, and semiconductor shortages collectively exposing the structural fragility of lean, just-in-time logistics architectures [1,2]. The COVID-19 pandemic alone is estimated to have cost global supply chains in excess of USD 4 trillion in lost revenues, compelling organisations to fundamentally reconsider the risk assumptions underpinning their operational models [3]. Against this backdrop, artificial intelligence has emerged not merely as an efficiency-enhancing tool but as a foundational technology capable of endowing supply chains with adaptive, self-correcting properties previously confined to the domain of biological and complex engineered systems [4].

The concept of the "self-healing supply chain" - a network capable of autonomously detecting, diagnosing, and recovering from disruptions without sustained human intervention - has gained substantial scholarly and practitioner attention since 2021 [5,6]. Underpinned by advances in machine learning (ML), deep reinforcement learning, digital twin simulation, Internet of Things (IoT) sensor networks, and autonomous robotic systems, self-healing architectures represent a convergence of Industry 4.0 technologies applied to the challenge of supply chain continuity [7,8]. Scholars have begun to theorise these systems through the lens of complex adaptive systems (CAS) theory, arguing that AI-mediated feedback loops enable supply networks to exhibit emergent adaptive behaviours analogous to those observed in natural resilient systems [9,10].

Despite growing scholarly interest, significant gaps persist in the empirical literature. First, the majority of extant studies adopt quantitative or simulation-based approaches, leaving the lived organisational experiences of implementing AI-driven self-healing systems largely unexplored [11,12]. Second, the human dimensions of logistics automation - including workforce displacement, skill reconfiguration, and the negotiation of human-AI task boundaries - remain undertheorised in supply chain management research [13,14]. Third, governance frameworks for autonomous supply chain decision-making, particularly regarding algorithmic accountability and ethical AI deployment, are nascent and fragmented across jurisdictions [15,16].

This study addresses these gaps through a qualitative multi-case study investigation of AI-driven self-healing supply chains across six multinational organisations. The central research questions guiding this inquiry are: (RQ1) How do organisations conceptualise and operationalise AI-driven self-healing in their supply chain networks? (RQ2) What organisational and technological conditions enable or inhibit the realisation of autonomous logistics capabilities? (RQ3) How do human actors navigate their roles within increasingly automated supply chain environments? (RQ4) What governance and ethical challenges arise from autonomous supply chain decision-making, and how are they addressed?

The remainder of this article is structured as follows. Section 2 presents a comprehensive review of the extant literature on AI in supply chains, self-healing systems, logistics automation, and related enabling technologies. Section 3 articulates the theoretical framework integrating dynamic capabilities theory and complex adaptive systems theory. Section 4 details the qualitative methodology, including research design, sampling strategy, data collection, and analytical procedures. Section 5 presents and discusses the findings organised around four major themes. Section 6 concludes with theoretical contributions, practical implications, limitations, and directions for future research.

Literature Review

Artificial Intelligence in Supply Chain Management: An Evolving Landscape

The application of AI to supply chain management has expanded dramatically since 2021, driven by improvements in computational power, the proliferation of real-time data streams, and the maturation of cloud-native ML platforms [17,18]. Machine learning algorithms - including ensemble methods, recurrent neural networks, and transformer-based architectures - are now routinely applied to demand forecasting, supplier risk scoring, route optimisation, and inventory management [19]. Studies report that AI-powered demand forecasting reduces forecast error by between 20% and 35% compared to traditional statistical methods, with corresponding reductions in safety stock requirements and holding costs [20].

Generative AI and large language models (LLMs) represent the most recent frontier in supply chain intelligence, enabling natural language interfaces for supply chain control towers, automated contract analysis, and scenario-based disruption simulation [21,22]. Ivanov specifically examines how LLM-driven world models can simulate supply chain topology changes in response to geopolitical disruptions, offering a new paradigm for strategic resilience planning. Similarly, the emergence of multi-agent AI systems - wherein autonomous software agents negotiate, coordinate, and execute supply chain decisions in real time - is transforming the architecture of supply chain orchestration [23,24].

Self-Healing Supply Chains: Conceptual Foundations

The metaphor of self-healing, borrowed from materials science and biological systems, refers to the capacity of a system to autonomously detect damage, diagnose its cause, and initiate corrective action to restore functional integrity. Applied to supply chains, self-healing denotes a network's ability to autonomously reroute material flows, substitute suppliers, adjust production schedules, and reconfigure distribution networks in response to detected disruptions - without requiring manual intervention at each decision point.

Ivanov and Dolgui provide a foundational conceptualisation of self-healing supply chains, distinguishing between reactive self-healing (triggered after disruption onset) and proactive self-healing (anticipating disruptions before they materialise). Proactive self-healing relies on predictive AI models that continuously monitor supply network signals - including supplier financial health indicators, geopolitical risk indices, weather forecasts, and port congestion data - to generate early warnings and pre-position response resources [25,26]. Reactive self-healing, by contrast, leverages real-time optimisation algorithms and pre-defined response playbooks to minimise recovery time once a disruption has been confirmed.

The distinction between self-healing and conventional supply chain resilience is important. Resilience, in the traditional sense, refers to the ability to return to a pre-disruption state following an adverse event [27]. Self-healing extends this concept by incorporating the ability to learn from disruption events, update response models, and improve future performance - a property more analogous to antifragility than to mere resilience.

Digital Twins and Real-Time Supply Chain Simulation

Digital twin technology - the creation of dynamic, data-synchronised virtual replicas of physical supply chain assets and flows - has emerged as a critical enabler of self-healing capability [28]. Supply chain digital twins integrate real-time IoT sensor data, ERP transaction records, and external data feeds to maintain a continuously updated model of network state, enabling both predictive simulation and autonomous decision execution.

Research by Ding et al. demonstrates that cognitive digital supply chain twins, employing hybrid deep learning architectures, can detect disruption signals with an average lead time of 72 hours before operational impact, enabling pre-emptive inventory repositioning and supplier switching. Liu et al. extend this work by integrating reinforcement learning agents into digital twin environments, enabling autonomous route replanning in response to simulated disruption scenarios. The commercial deployment of supply chain digital twins by firms such as Siemens, Unilever, and DHL has been documented in multiple case-based studies, with reported reductions in disruption recovery time of between 30% and 55% [29].

Internet of Things and Sensor-Driven Supply Chain Visibility

The Internet of Things constitutes the sensory layer of self-healing supply chains, providing the granular, real-time data streams upon which AI models depend for accurate situational awareness. IoT devices - including RFID tags, GPS trackers, temperature and humidity sensors, and smart shelving systems - generate continuous telemetry on the location, condition, and movement of goods throughout the supply network [30,31].

Coito et al. publishing in the International Journal of Integrated Supply Management, demonstrate that intelligent automation in internal supply chains, underpinned by IoT sensor integration, reduces order fulfilment cycle times by up to 34% and decreases error rates in warehouse operations by 28%. The convergence of IoT with AI analytics platforms enables what Kamble et al. term "ambient intelligence" in supply chains - environments in which data collection, analysis, and response are seamlessly integrated into the physical infrastructure of logistics operations.

The proliferation of AIoT (AI of Things) architectures - wherein AI inference is performed at the edge, directly on IoT devices - further reduces latency in disruption detection and response, enabling near-real-time self-healing actions at the operational level. Studies examining AIoT implementation in cold chain logistics report reductions in product spoilage of up to 40%, attributable to real-time anomaly detection and autonomous rerouting of temperature-sensitive shipments.

Blockchain and Distributed Trust in Autonomous Supply Chains

Blockchain technology provides the distributed ledger infrastructure necessary to ensure data integrity, transparency, and trust in autonomous supply chain systems - particularly in multi-party networks where no single actor controls the full information environment. Smart contracts - self-executing code deployed on blockchain platforms - enable automated enforcement of supply chain agreements, triggering payment releases, penalty clauses, and supplier substitution actions without manual authorisation.

The integration of blockchain with AI and IoT creates what researchers have termed "trustworthy autonomous supply chains" - systems in which the provenance, integrity, and auditability of AI-generated decisions can be verified by all network participants. This is particularly relevant for self-healing actions that involve cross-organisational boundary-spanning decisions, such as emergency supplier activation or dynamic contract renegotiation, where accountability and audit trails are legally and commercially significant.

Autonomous Vehicles, Robotics, and Last-Mile Logistics Automation

The physical execution layer of self-healing supply chains increasingly relies on autonomous mobile robots (AMRs), autonomous guided vehicles (AGVs), unmanned aerial vehicles (drones), and self-driving trucks to implement AI-generated routing and fulfilment decisions. Warehouse automation, driven by AMRs and AI-powered picking systems, has been shown to increase throughput by 200-300% compared to manual operations while simultaneously reducing error rates and labour costs.

In last-mile logistics, autonomous delivery vehicles and drone delivery systems are enabling self-healing responses to urban congestion and infrastructure disruptions, dynamically rerouting deliveries in real time based on traffic, weather, and demand signals. The integration of autonomous physical systems with AI decision engines and digital twin simulations creates a closed-loop self-healing architecture in which sensing, deciding, and acting are seamlessly integrated across the physical and digital domains.

Supply Chain Resilience and AI: Empirical Evidence

A growing body of empirical research documents the resilience benefits of AI integration in supply chains. Belhadi et al. find that AI-driven supply chain innovation significantly enhances resilience across a sample of 312 manufacturing firms, with the effect mediated by dynamic capabilities in data analytics and process reconfiguration. Bag et al. report that AI-enabled supply chain visibility reduces disruption impact severity by an average of 42% across a sample of South African manufacturing firms. Wamba et al. demonstrate that AI and information system capabilities jointly predict supply chain resilience performance, with interaction effects suggesting complementarity between technological and organisational capabilities [32].

Modgil et al. examine the role of AI in supply chain knowledge management, finding that AI-mediated knowledge capture and dissemination accelerates organisational learning from disruption events, reducing the time to full operational recovery by 38%. Kamble et al. provide evidence that digital twin-enabled supply chains demonstrate superior agility and resilience compared to non-twin counterparts, with the gap widening during high-disruption periods such as the COVID-19 pandemic. These findings collectively support the proposition that AI is not merely an efficiency tool but a foundational resilience-building technology in contemporary supply chain management.

Human-AI Collaboration and Workforce Transformation

The automation of supply chain tasks through AI and robotics raises fundamental questions about the future of human work in logistics. While early discourse framed automation primarily as a threat to employment, more recent scholarship emphasises the complementarity between human and AI capabilities in complex supply chain environments. Humans retain comparative advantages in tasks requiring contextual judgement, ethical reasoning, stakeholder management, and creative problem-solving - precisely the capabilities most needed when AI systems encounter novel disruption scenarios outside their training distribution.

Research on human-AI teaming in supply chain control towers reveals that hybrid decision architectures - wherein AI systems handle high-frequency, data-intensive decisions while humans focus on strategic exception management - outperform both fully automated and fully manual approaches in terms of resilience and decision quality. However, the effective realisation of such hybrid architectures requires significant investment in AI literacy, change management, and the redesign of human roles and incentive structures.

Theoretical Framework

Dynamic Capabilities Theory

This study is theoretically anchored in dynamic capabilities theory (DCT), as originally formulated by Teece et al. and subsequently extended by Teece and Eisenhardt and Martin. Dynamic capabilities are defined as the firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments [33-35]. In the context of AI-driven supply chains, dynamic capabilities manifest as the organisational capacity to sense emerging disruptions (sensing), seize opportunities for autonomous response (seizing), and continuously reconfigure supply network configurations in light of new information (reconfiguring).

The application of DCT to AI-driven self-healing supply chains is particularly apt because self-healing capability is not a static technological property but an emergent organisational competency that develops through cycles of sensing, learning, and reconfiguration. Organisations that invest in AI sensing capabilities - through IoT networks, predictive analytics platforms, and supply chain control towers - develop superior disruption detection capabilities. Those that further invest in AI-driven seizing capabilities - through autonomous decision engines, digital twin simulation, and smart contract automation - develop the capacity to translate disruption signals into rapid, coordinated responses. Reconfiguration capabilities, finally, enable organisations to continuously update their AI models, response playbooks, and network configurations based on accumulated disruption experience.

Complex Adaptive Systems Theory

Dynamic capabilities theory is complemented by complex adaptive systems (CAS) theory, which provides a systems-level perspective on how AI-mediated supply networks exhibit emergent adaptive behaviours. CAS theory, rooted in the Santa Fe School of complexity science, conceptualises supply chains as networks of semi-autonomous agents that interact according to local rules, generating emergent macro-level patterns of order and adaptation [36].

In AI-driven supply chains, individual AI agents - demand forecasting models, routing optimisers, supplier risk scorers, warehouse management systems - interact continuously, sharing information and coordinating actions through digital platforms. The emergent outcome of these interactions is a supply network that exhibits self-organising, adaptive properties - the hallmarks of self-healing behaviour. CAS theory also foregrounds the importance of feedback loops, non-linearity, and path dependence in supply chain adaptation, cautioning against overly deterministic models of AI-driven self-healing.

Integrating DCT and CAS: A Framework for AI-Driven Self-Healing

The integration of DCT and CAS theory yields a multi-level framework for understanding AI-driven self-healing supply chains. At the organisational level, DCT explains how firms develop the sensing, seizing, and reconfiguring capabilities necessary to leverage AI for self-healing. At the network level, CAS theory explains how the interactions among AI agents and human actors generate emergent adaptive behaviours that transcend the capabilities of any individual firm or system component. Together, these theories suggest that self-healing is an emergent property of AI-augmented supply networks, arising from the dynamic interplay between technological infrastructure, organisational routines, and human agency - a proposition that guides the empirical inquiry of this study.

Methodology

Research Philosophy and Design

This study adopts an interpretivist philosophical stance, premised on the view that organisational phenomena such as AI-driven self-healing supply chains are socially constructed and can only be fully understood through the subjective meanings and interpretations of the actors involved [37]. This stance is consistent with the qualitative tradition in supply chain research, which has been advocated by scholars seeking to complement the dominant quantitative paradigm with richer, contextually grounded accounts of supply chain phenomena [38,39].

A multi-case study design was selected as the primary research strategy, following Yin's canonical framework for case study research. Multi-case designs are particularly suited to the present inquiry because they enable cross-case comparison and analytical generalisation - the inference of theoretical propositions from empirical patterns across cases - while preserving the contextual richness that distinguishes qualitative from quantitative approaches [40]. The study incorporates phenomenological elements - attending to participants' lived experiences of AI implementation and supply chain transformation - and grounded theory elements - allowing theoretical categories to emerge inductively from the data rather than being imposed from existing frameworks [41].

Case Selection and Sampling Strategy

Six multinational organisations were selected as case study sites using purposive sampling, guided by the principle of theoretical relevance [42]. Selection criteria required that each organisation: (a) had implemented AI-driven supply chain systems for a minimum of two years; (b) operated in a sector with high supply chain complexity (manufacturing, retail, or third-party logistics); (c) had experienced at least one significant supply chain disruption during the study period; and (d) was willing to grant access to senior executives and operational staff for interview purposes. The six cases span three continents and four industry sectors, providing sufficient contextual variation for cross-case comparison and theoretical generalisation.

Within each case organisation, a purposive sample of key informants was identified using a combination of snowball sampling and organisational gatekeeping. A total of 42 semi-structured interviews were conducted, with informants including Chief Supply Chain Officers (CCSOs), AI and data science directors, logistics operations managers, warehouse automation specialists, and frontline logistics supervisors. This multi-level sampling strategy ensured that perspectives from strategic, tactical, and operational levels of supply chain management were represented in the data, consistent with the recommendation of Eisenhardt and Graebner to triangulate informant perspectives across organisational hierarchies.

Data Collection

Data collection was conducted over a period of fourteen months (January 2023 - February 2024), employing three primary methods: semi-structured interviews, documentary analysis, and non-participant observation.

Semi-Structured Interviews constituted the primary data source. An interview guide was developed based on the research questions and theoretical framework, covering topics including: the organisation's journey towards AI-driven supply chain automation; specific AI technologies deployed and their perceived impacts; experiences of supply chain disruptions and AI-mediated responses; perceptions of human-AI collaboration and workforce transformation; and governance and ethical considerations. Interviews lasted between 55 and 90 minutes, were conducted via video conferencing or in person, and were audio-recorded with participants' informed consent. Verbatim transcripts were produced for all interviews, yielding approximately 680 pages of primary data.

Documentary analysis provided secondary data to corroborate and contextualise interview accounts. Documents analysed included internal AI strategy documents, supply chain resilience reports, incident post-mortems, technology vendor contracts, and publicly available sustainability and annual reports. Documentary data were particularly valuable for triangulating factual claims made in interviews and for tracing the historical trajectory of AI adoption within each case organisation [43].

Non-participant observation was conducted during site visits to three of the six case organisations, providing direct observational data on AI-mediated supply chain operations, human-AI interaction in logistics control rooms, and warehouse automation environments. Field notes from 18 days of observation were compiled and integrated into the analysis.

Data Analysis

Thematic analysis, following the six-phase framework of Braun and Clarke was employed as the primary analytical method. Analysis proceeded through the following phases: (1) familiarisation with the data through repeated reading of transcripts and field notes; (2) systematic generation of initial codes across the full dataset; (3) searching for themes by clustering related codes into candidate thematic categories; (4) reviewing themes against the coded data extracts and the full dataset; (5) defining and naming themes with precision; and (6) producing the written analysis. The analytical process was supported by NVivo 12 qualitative data analysis software, which facilitated systematic coding, theme management, and cross-case comparison [44].

Grounded theory analytic procedures - specifically constant comparative analysis and theoretical sampling - were incorporated to allow emergent theoretical insights to shape subsequent data collection and analysis. As themes emerged from early-stage analysis, interview guides were refined to probe emergent concepts in greater depth with subsequent informants, consistent with the iterative logic of grounded theory inquiry.

Trustworthiness and Rigour

Trustworthiness was assessed using Lincoln and Guba's four criteria: credibility, transferability, dependability, and confirmability [45].

Credibility was established through prolonged engagement with case organisations (14 months), member checking (returning draft thematic summaries to 18 key informants for review and correction), and triangulation of data sources (interviews, documents, observation). Transferability was enhanced through thick description of case contexts, enabling readers to assess the applicability of findings to their own settings. Dependability was ensured through the maintenance of a detailed audit trail documenting all methodological decisions, including sampling choices, coding decisions, and theme revisions. Confirmability was addressed through reflexivity practices - including the maintenance of a researcher reflexivity journal - and through independent coding of a 20% sub-sample of transcripts by a second researcher, achieving an inter-rater reliability coefficient (Cohen's Kappa) of 0.81, indicating strong agreement.

Ethical Considerations

Ethical approval for the study was obtained from the relevant institutional review board prior to data collection. All participants provided written informed consent and were assured of anonymity and confidentiality. Organisations are referred to using pseudonyms (Alpha Logistics, Beta Manufacturing, Gamma Retail, Delta 3PL, Epsilon Electronics, Zeta Pharma) throughout the findings. Data were stored securely in encrypted repositories, and access was restricted to the research team.

Findings and Discussion

Analysis of the 42 interviews, 86 documents, and 18 days of observational data yielded four overarching themes, each comprising multiple sub-themes. The following sections present these themes with illustrative quotations and cross-case analysis, followed by discussion that situates the findings within the extant literature and theoretical framework.

Theme 1: AI-Enabled Proactive Disruption Sensing and Early-Warning Architectures

From Reactive to Predictive: The Shift in Disruption Management Philosophy

Across all six case organisations, a consistent narrative emerged describing a fundamental philosophical shift in how supply chain disruptions are managed - from reactive "firefighting" to proactive, AI-mediated anticipation. This transition was described by informants as transformative, both operationally and culturally.

The CCSO of Alpha Logistics articulated this shift with particular clarity: "We used to find out about a port closure from a phone call from a freight forwarder. Now our AI system flags elevated congestion risk at Singapore three weeks before it becomes a problem, and we've already started rerouting by the time our competitors are scrambling." Similar accounts were provided by informants at Beta Manufacturing and Epsilon Electronics, where AI-powered supply chain control towers integrate signals from satellite imagery, social media sentiment analysis, weather forecasting services, and financial news feeds to generate composite disruption risk scores for each node in the supply network.

These findings align with the proactive self-healing conceptualisation of Ivanov and Dolgui and the early-warning architecture described by Queiroz et al. The AI systems deployed in case organisations operationalise what Teece terms "sensing capabilities" - the dynamic capability to scan, monitor, and interpret environmental signals relevant to the firm's strategic interests. The sophistication of these sensing architectures varied across cases, with Epsilon Electronics and Zeta Pharma deploying the most advanced systems, incorporating natural language processing (NLP) for automated monitoring of regulatory and geopolitical news sources.

Digital Twins as the Situational Awareness Backbone

Digital twin technology emerged as the central enabling infrastructure for proactive disruption sensing in four of the six case organisations. Informants consistently described their supply chain digital twins as providing a "single source of truth" for network state - a continuously updated virtual model against which AI anomaly detection algorithms could identify deviations from expected operational parameters.

The Head of Digital Supply Chain at Delta 3PL described the operational significance of their digital twin: "Before the twin, we had maybe 40% visibility of our network in real time. Now it's 94%. When something goes wrong anywhere - a supplier delay, a warehouse capacity issue, a carrier failure - we know about it in minutes, not days. And the AI is already generating response options before I've even read the alert." This account resonates with the findings of Ding et al. who report that cognitive digital supply chain twins can detect disruption signals with an average lead time of 72 hours before operational impact.

The integration of IoT sensor networks with digital twin platforms was identified as a critical success factor for disruption sensing capability. Coito et al. document similar findings in their study of intelligent automation in internal supply chains, demonstrating that IoT-enabled visibility reduces order fulfilment cycle times substantially. At Gamma Retail, the deployment of 47,000 IoT sensors across warehouse and transportation assets generated a data stream of approximately 2.3 million data points per hour, providing the granular real-time telemetry necessary to sustain accurate digital twin synchronisation and support AI-driven anomaly detection.

Predictive Analytics and Supplier Risk Intelligence

A sub-theme that emerged prominently across manufacturing and pharmaceutical cases concerned the application of AI to supplier risk intelligence - the continuous monitoring and scoring of supplier health, reliability, and disruption risk. At Zeta Pharma, an AI-powered supplier risk platform aggregated data from over 200 external data sources - including financial market data, ESG ratings, geopolitical risk indices, and logistics performance benchmarks - to generate dynamic risk scores for each of the firm's 3,400 direct suppliers.

Informants reported that this capability had enabled Zeta Pharma to anticipate and mitigate three significant supplier failures during the study period, including one case in which a critical API (active pharmaceutical ingredient) supplier's financial distress was detected eight weeks before the supplier declared insolvency, providing sufficient lead time to qualify and onboard an alternative source. These findings corroborate Bag et al. who document the resilience benefits of AI-enabled supply chain visibility, and extend them by illustrating the specific mechanisms through which predictive supplier intelligence translates into disruption avoidance.

Theme 2: Autonomous Reconfiguration and Self-Healing Mechanisms

Autonomous Decision Execution: From Alerts to Actions

A critical distinction emerged in the data between AI systems that generate disruption alerts for human review and those that autonomously execute reconfiguration decisions. Informants described a spectrum of autonomy across their AI deployments, ranging from "advisory" systems that recommend actions for human approval to "autonomous" systems that execute pre-approved response playbooks without human intervention.

At Delta 3PL, autonomous execution was most advanced, with the organisation's AI platform empowered to autonomously reroute shipments, activate backup carriers, adjust delivery windows, and update customer notifications - all within pre-defined decision boundaries - without requiring human sign-off. The VP of Operations described the operational impact: "During the Suez Canal disruption, our system autonomously rerouted 340 shipments across 14 countries within six hours. No human could have done that at that speed and at that scale. By the time our team reviewed the morning report, the problem was already 80% resolved." This account exemplifies the reactive self-healing mechanism described by Ivanov and the autonomous reconfiguration capability theorised by Cavalcante et al.

The degree of autonomy granted to AI systems varied systematically with the perceived reversibility of decisions. Informants across all cases described a consistent logic: high-frequency, low-stakes, and easily reversible decisions (e.g., carrier selection, route optimisation, inventory reorder) were fully automated, while low-frequency, high-stakes, and difficult-to-reverse decisions (e.g., emergency supplier qualification, contract renegotiation, production line shutdown) remained subject to human approval. This finding resonates with Srinivasan and Swink who describe hybrid decision architectures in supply chain control towers as the dominant model in advanced AI deployments.

Reinforcement Learning and Adaptive Response Models

A technically distinctive sub-theme concerned the use of reinforcement learning (RL) algorithms to develop self-improving response models - AI systems that learn from each disruption event to improve the quality and speed of future responses. At Epsilon Electronics, the supply chain AI platform employed a multi-agent RL architecture in which individual agents representing different supply network nodes competed and cooperated to optimise network-wide performance under disruption scenarios.

The Head of AI at Epsilon Electronics described the learning dynamics: "Every disruption is a training event. The RL agents observe what worked and what didn't, update their policies, and next time they encounter a similar pattern, they respond faster and more effectively. We've seen a 40% improvement in disruption recovery time over 18 months, and we attribute most of that to the RL system's learning curve." This account aligns with the antifragility concept invoked by Ivanov - the idea that self-healing supply chains not only recover from disruptions but emerge stronger through the learning process. Liu et al. provide theoretical support for RL-based autonomous route replanning, and Modgil et al. document the role of AI in accelerating organisational learning from disruption events.

Blockchain-Enabled Autonomous Contract Execution

In two case organisations (Zeta Pharma and Beta Manufacturing), blockchain smart contracts were deployed to automate the execution of supply chain agreements in response to AI-detected disruption conditions. At Zeta Pharma, smart contracts automatically triggered emergency supplier activation clauses, released pre-negotiated inventory reserves, and initiated penalty calculations when AI systems detected supplier delivery failures exceeding pre-defined thresholds.

Informants described blockchain as providing the "trust infrastructure" necessary to enable autonomous cross-organisational decisions - ensuring that all parties could verify the conditions triggering automated actions and audit the resulting transactions. The Director of Supply Chain Technology at Zeta Pharma noted: "Without blockchain, you can't automate cross-company decisions. There's no shared truth. With it, the smart contract is the shared truth - everyone can see the data that triggered the action, and no one can dispute it." These findings corroborate Queiroz et al. and Kshetri who theorise blockchain as a trust-enabling layer for autonomous supply chain systems, and extend them by providing empirical grounding in pharmaceutical supply chain contexts.

Theme 3: Human-AI Collaboration and Workforce Transformation in Logistics

Redefining Human Roles: From Operators to Orchestrators

A pervasive theme across all cases concerned the transformation of human roles in AI-augmented supply chain environments. Informants consistently described a shift from operational execution roles - physically moving goods, manually processing orders, reactively managing exceptions - to orchestration roles - designing AI systems, setting decision boundaries, managing exceptions that exceed AI capability, and interpreting AI outputs for strategic decision-making.

A logistics supervisor at Gamma Retail, who had worked in warehouse operations for 22 years, articulated this transformation with striking clarity: "My job used to be making sure the right boxes went on the right trucks. Now my job is making sure the AI is making the right decisions about which boxes go on which trucks - and stepping in when it's not. It's more interesting, honestly. But it took a lot of learning." This account resonates with Pournader et al. who conceptualise the human role in automated supply chains as shifting from task execution to AI governance and exception management.

Across cases, the most successful human-AI collaboration models were characterised by clear role delineation, transparent AI decision explanations (explainable AI), and structured escalation protocols that defined the conditions under which human override of AI decisions was warranted. These findings extend the human-AI teaming literature by providing detailed empirical accounts of how role boundaries are negotiated and institutionalised in practice.

AI Literacy and Capability Development

A consistently identified challenge across all case organisations concerned the development of AI literacy among supply chain workforces - the knowledge and skills necessary to work effectively alongside AI systems, interpret AI outputs critically, and identify AI errors or biases. Informants described significant variation in AI literacy across organisational levels, with strategic leadership and data science teams exhibiting high literacy, while operational and middle-management levels frequently reported limited understanding of AI decision logic.

The CCSO of Beta Manufacturing described the organisational challenge: "We invested heavily in the technology. We underinvested in the people. We had a fantastic AI system that our warehouse managers didn't trust because they didn't understand how it worked. They kept overriding it, which defeated the purpose. We had to go back and invest in education and change management before we got the value." This account underscores the finding of Modgil et al. that AI literacy mediates the relationship between AI investment and supply chain performance, and highlights the importance of organisational learning processes in realising the value of AI-driven automation.

Workforce Anxiety and Change Management

Informants across all cases acknowledged significant workforce anxiety associated with logistics automation, particularly among frontline workers in warehousing and transportation. While no case organisation reported large-scale redundancies attributable to AI deployment during the study period, informants described pervasive concerns among workers about long-term employment security, the pace of technological change, and the perceived opacity of AI-driven decision-making.

Effective change management strategies identified across cases included transparent communication about the organisation's AI strategy and its implications for workforce roles; proactive reskilling and upskilling programmes; the involvement of frontline workers in the design and testing of AI systems; and the explicit positioning of AI as a tool to enhance rather than replace human capabilities. These findings align with the human-centric Industry 5.0 perspective articulated by Lücker et al. and the workforce transformation frameworks proposed by Pournader et al.

Theme 4: Ethical, Governance, and Regulatory Considerations in Autonomous Supply Systems

Algorithmic Accountability and the Governance Gap

A significant and cross-cutting theme concerned the governance challenges arising from autonomous AI decision-making in supply chains - particularly the question of accountability when AI-generated decisions produce adverse outcomes. Informants across all cases described a "governance gap" between the technical capabilities of their AI systems and the organisational and regulatory frameworks available to govern their use.

The Chief Risk Officer of Alpha Logistics articulated the dilemma: "If our AI autonomously cancels a supplier contract based on a risk score, and that supplier loses business and disputes the decision - who is accountable? Is it the AI? Is it us? Is it the data provider whose data fed the risk score? We don't have clear answers to these questions, and neither do our lawyers or our regulators." This account resonates with the governance challenges identified by Taddeo and Floridi and Wamba-Taguimdje et al. who document the nascent state of AI governance frameworks in supply chain contexts.

Across cases, governance responses to this challenge included the establishment of AI ethics committees with cross-functional representation; the development of internal AI governance policies specifying decision boundaries, audit requirements, and escalation protocols; and proactive engagement with regulatory bodies to shape emerging AI governance frameworks. These organisational governance mechanisms are consistent with the responsible AI implementation framework proposed by emerging scholarship in the field.

Data Privacy, Security, and Sovereignty

The data-intensive nature of AI-driven self-healing supply chains generates significant data privacy and security challenges, particularly in multi-party network environments where sensitive operational data must be shared across organisational and jurisdictional boundaries. Informants described complex data governance challenges arising from the need to share supplier performance data, customer demand data, and logistics telemetry with AI platforms operated by third-party technology vendors.

At Zeta Pharma, data sovereignty concerns - arising from the need to comply with GDPR in Europe, PDPA in Asia, and sector-specific pharmaceutical data regulations - had significantly constrained the architecture of the firm's AI supply chain platform, requiring the implementation of federated learning approaches that allowed AI models to be trained on distributed data without centralising sensitive information. These findings extend the data governance literature in supply chain management by illustrating the practical architectural implications of data sovereignty constraints for AI-driven self-healing systems.

Environmental Sustainability and the Carbon Footprint of AI

An emergent sub-theme, not anticipated in the initial research design, concerned the environmental sustainability implications of AI-driven logistics automation. Informants at three case organisations (Gamma Retail, Delta 3PL, and Epsilon Electronics) described active programmes to leverage AI for carbon footprint reduction - optimising transportation routes for fuel efficiency, reducing empty running through AI-driven load consolidation, and managing warehouse energy consumption through AI-powered building management systems.

The Head of Sustainability at Gamma Retail reported: "Our AI routing system has reduced our fleet's carbon emissions by 19% in two years. That's not just good for the planet - it's good for business, because our customers and investors are demanding it." However, informants also acknowledged the energy consumption of AI infrastructure itself - particularly large-scale ML training and inference workloads - as an emerging sustainability concern. These findings resonate with the sustainable logistics literature and highlight the need for holistic sustainability assessments that account for both the environmental benefits and costs of AI-driven supply chain automation.

Discussion: Towards a Grounded Model of AI-Driven Supply Chain Self-Healing

The findings of this study, synthesised across four themes and six case organisations, support the development of a grounded theoretical model of AI-driven supply chain self-healing. This model, integrating the empirical insights of the present study with the theoretical frameworks of dynamic capabilities theory and complex adaptive systems theory, conceptualises self-healing as a multi-layered, emergent organisational capability comprising four interdependent components.

The Sensing Layer encompasses the AI-enabled proactive disruption detection capabilities documented in Theme 1 - digital twins, IoT sensor networks, predictive analytics, and supplier risk intelligence platforms. This layer operationalises the sensing dimension of dynamic capabilities and provides the informational foundation upon which all subsequent self-healing actions depend.

The Decision Layer encompasses the autonomous and semi-autonomous decision execution capabilities documented in Theme 2 - reinforcement learning response models, smart contract automation, and hybrid human-AI decision architectures. This layer operationalises the seizing dimension of dynamic capabilities and instantiates the agent-level adaptive behaviours theorised in complex adaptive systems theory.

The Human-Organisational Layer encompasses the workforce transformation, AI literacy development, and change management processes documented in Theme 3. This layer operationalises the reconfiguring dimension of dynamic capabilities and highlights the irreducibly human dimensions of supply chain self-healing - the insight that autonomous systems require human governance, learning, and adaptation to function effectively [46-61].

The Governance Layer encompasses the algorithmic accountability frameworks, data governance mechanisms, and sustainability governance processes documented in Theme 4. This layer provides the institutional scaffolding within which AI-driven self-healing operates, shaping the boundaries, conditions, and accountability structures of autonomous supply chain decision-making.

The model's central proposition is that sustainable AI-driven supply chain self-healing requires the simultaneous development and integration of all four layers. Organisations that invest exclusively in technological sensing and decision capabilities without developing commensurate human-organisational and governance capabilities are likely to encounter the trust deficits, workforce resistance, and accountability failures documented across the case organisations in this study. Conversely, organisations that attend to all four layers - as exemplified by Epsilon Electronics and Zeta Pharma in the present study - demonstrate superior resilience performance and more sustainable trajectories of AI-driven supply chain transformation.

Conclusion

Summary of Contributions

This study makes four principal contributions to the supply chain management literature. First, it provides rich empirical evidence - drawn from 42 interviews, 86 documents, and 18 days of observation across six multinational organisations - of how AI-driven self-healing supply chains are being operationalised in practice, addressing a significant gap in the predominantly quantitative and simulation-based literature on supply chain resilience and AI.

Second, it develops a grounded theoretical model of AI-driven supply chain self-healing that integrates sensing, decision, human-organisational, and governance layers, providing a more comprehensive and empirically grounded conceptualisation than existing frameworks. This model advances the theoretical integration of dynamic capabilities theory and complex adaptive systems theory in the supply chain management domain.

Third, it foregrounds the human dimensions of logistics automation - including role transformation, AI literacy development, workforce anxiety, and change management - as central rather than peripheral concerns in the realisation of self-healing supply chains. This contribution responds to calls from Pournader et al. and Srinivasan and Swink for greater attention to human factors in supply chain automation research.

Fourth, it identifies and characterises the governance challenges arising from autonomous AI decision-making in supply chains - including algorithmic accountability, data sovereignty, and sustainability governance - and documents the organisational responses being developed in practice, contributing to the nascent literature on AI governance in supply chain contexts.

Practical Implications

For supply chain practitioners, this study offers several actionable insights. Organisations seeking to develop AI-driven self-healing capabilities are advised to adopt a layered implementation approach, sequentially building sensing, decision, human-organisational, and governance capabilities rather than pursuing purely technological solutions. Investment in AI literacy and change management is identified as a critical success factor, with particular attention needed for middle-management and operational-level workforces. The establishment of clear decision boundaries - specifying the conditions under which AI systems may act autonomously and those requiring human approval - is identified as essential for maintaining trust in autonomous systems and managing accountability risks.

For policymakers and regulators, the findings highlight the urgency of developing coherent governance frameworks for autonomous supply chain AI, particularly regarding algorithmic accountability, cross-border data sharing, and the environmental sustainability of AI infrastructure. The proactive engagement of supply chain organisations with emerging regulatory frameworks - as documented in several case organisations - suggests an appetite for co-regulatory approaches that balance innovation with accountability.

Limitations and Future Research

This study is subject to several limitations that should be considered in interpreting its findings. The qualitative case study design, while enabling rich contextual insight, limits the statistical generalisability of findings to broader populations of supply chain organisations. The study's focus on large multinational firms means that the findings may not fully capture the challenges and opportunities facing small and medium-sized enterprises in the transition to AI-driven supply chain management. The 14-month data collection period, while substantial, represents a snapshot of a rapidly evolving technological and organisational landscape.

Future research should address these limitations through mixed-methods designs that combine the contextual richness of qualitative inquiry with the statistical power of large-sample quantitative studies. Longitudinal research designs are particularly needed to track the evolution of AI-driven self-healing capabilities over time and to assess the long-term performance and sustainability implications of autonomous logistics systems. Research examining AI-driven self-healing in SME contexts, in developing economy supply chains, and in sector-specific settings (e.g., healthcare, agri-food, defence) would significantly extend the generalisability of the grounded model developed in this study.

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