# The Impact of Artificial Intelligence on Supply Chain Resilience: A Study of AI-Based Demand Forecasting and Inventory Optimization

[1]Dr. Pooja Sharma
[1]GLS University, Ahmedabad (Gujarat)

*Abstract*—**Global supply chains have been subjected to an unprecedented sequence of shocks over the past several years, from the COVID-19 pandemic to geopolitical conflict, trade policy uncertainty, and extreme-weather events, exposing the fragility of lean, just-in-time operating models and elevating supply chain resilience to a board-level priority. Artificial intelligence (AI) has emerged as one of the most widely discussed enablers of resilience, with machine learning, deep learning, and, more recently, generative AI and large language models being deployed across demand forecasting, inventory optimization, risk detection, and logistics coordination. This paper presents a structured literature review of the relationship between AI adoption and supply chain resilience, with particular emphasis on two of its most mature application domains: AI-based demand forecasting and AI-based inventory optimization. Drawing on approximately fifty peer-reviewed articles, conference papers, and industry reports published primarily between 2020 and 2026, the review synthesizes evidence on how AI technologies improve forecast accuracy, reduce stockouts and overstocking, and support the visibility, agility, and viability capabilities associated with resilient supply chains, including during the COVID-19 disruption. The review also consolidates the benefits reported in the literature—cost reduction, error reduction, and faster decision cycles—alongside recurring challenges, including data quality and integration, the black-box or low-explainability nature of many AI models, high implementation costs, workforce resistance, and a persistent research gap concerning the long-term, human-centric, and multi-tier integration of AI within resilient supply chain ecosystems. Building on these findings, the paper proposes a conceptual framework linking AI-enabled forecasting and inventory capabilities to supply chain resilience outcomes, and concludes with managerial implications and directions for future empirical research.**

*Index Terms*—**artificial intelligence, supply chain resilience, demand forecasting, inventory optimization, machine learning, COVID-19, digital supply chain twin, explainable AI**

## I. Introduction

Supply chains have entered a period of sustained volatility. The COVID-19 pandemic disrupted production, transportation, and labor markets simultaneously and at global scale, exposing the limits of supply chain designs optimized primarily for cost efficiency rather than for resilience (Ivanov, 2020; Ivanov & Dolgui, 2020). Since 2020, supply chain leaders have faced a compounding set of disruptions—shipping bottlenecks, semiconductor shortages, the Russia–Ukraine conflict, Red Sea shipping disruptions, and recurring extreme-weather events—that have kept supply chain risk at the center of corporate strategy. In this environment, supply chain resilience, commonly understood as the capacity of a supply chain to anticipate, absorb, respond to, and recover from disruptive events while maintaining continuity of operations (Christopher & Peck, 2004; Ponomarov & Holcomb, 2009), has moved from an academic construct to an operational imperative.

Artificial intelligence (AI) has simultaneously matured from a largely experimental technology into a core component of enterprise supply chain systems. Machine learning models are now embedded in demand planning software, deep learning and reinforcement learning techniques are used to optimize multi-echelon inventory policies, and, since 2023, generative AI and large language models (LLMs) have begun to be layered on top of these systems to support natural-language decision support, scenario analysis, and supply chain risk narration (Jackson et al., 2024; Simchi-Levi et al., 2026). Industry surveys suggest that adoption is accelerating rapidly: more than 90 percent of Fortune 500 companies are reported to have adopted some form of AI tooling, and AI applications in supply chains have been associated with reductions in forecasting error of up to 50 percent and reductions in end-to-end supply chain costs of around 25 percent (as cited in recent operations-research literature; see also Deloitte's 2024 executive survey reported in Supply Chain Dive, 2025). At the same time, systematic reviews caution that the evidence base remains fragmented across disconnected technology types, industry contexts, and disciplinary perspectives (Smyth & Dennehy, 2024; Zamani, Smyth, Gupta, & Dennehy, 2023).

Two application domains have received particular attention in this literature: AI-based demand forecasting and AI-based inventory optimization. Demand forecasting is widely regarded as the starting point of supply chain planning, and machine learning approaches—ranging from gradient-boosted trees to deep learning architectures such as long short-term memory (LSTM) networks—have been shown in numerous studies to outperform traditional statistical methods such as ARIMA and exponential smoothing, particularly for retail and fast-moving consumer goods contexts characterized by promotions, seasonality, and intermittent demand (Huber & Stuckenschmidt, 2020; Mitra et al., 2022; Petropoulos, Grushka-Cockayne, Siemsen, & Spiliotis, 2022). Inventory optimization, in turn, has been transformed by the application of deep reinforcement learning and prescriptive analytics to multi-product, multi-echelon replenishment problems that were previously intractable using classical inventory theory alone (He, Zhang, & Ren, 2021; Wang, Peng, & Yang, 2022). Because forecasting errors propagate directly into inventory decisions—and inventory decisions, in turn, determine an organization's ability to absorb demand and supply shocks—these two capabilities are widely theorized as central mechanisms through which AI contributes to supply chain resilience (Naz, Kumar, Majumdar, & Agrawal, 2022; Dey, Chowdhury, Abadie, Vann Yaroson, & Sarkar, 2024).

Despite this growing body of work, the literature linking AI specifically to supply chain resilience—as opposed to supply chain efficiency or performance more broadly—remains comparatively young and dispersed. Existing systematic reviews have begun to map this terrain (Zamani et al., 2023; Naz et al., 2022; Samuels, 2024), but questions remain regarding which AI capabilities most directly strengthen resilience dimensions such as visibility, agility, redundancy, and collaboration; how the evidence generated during the COVID-19 pandemic generalizes to non-pandemic disruptions; and how organizations should navigate the practical barriers—data quality, explainability, cost, and workforce readiness—that continue to constrain AI adoption (Baryannis, Validi, Dani, & Antoniou, 2019; Olan, Spanaki, Ahmed, & Zhao, 2024).

This paper addresses these questions through a structured literature review. Its objectives are threefold: first, to synthesize the literature on AI applications in supply chain management with specific attention to demand forecasting and inventory optimization; second, to evaluate the evidence linking these AI applications to supply chain resilience outcomes, including the accelerated adoption evidence generated during COVID-19; and third, to identify the principal benefits, challenges, and research gaps in this literature and to propose a conceptual framework that can guide future empirical research. The remainder of the paper proceeds as follows. Section 2 describes the literature review methodology. Section 3 presents the literature review across seven thematic areas. Section 4 discusses the findings, identifies research gaps, and presents a conceptual framework. Section 5 concludes with managerial implications and directions for future research.

## II. Research Methodology (Literature Review Method)

This paper adopts a structured, narrative literature review methodology, informed by the systematic review conventions increasingly used in the supply chain management field (e.g., Samuels, 2024; Zamani et al., 2023), while retaining the flexibility of a narrative synthesis appropriate for a conceptual, discussion-oriented paper. Relevant literature was identified through keyword searches combining terms such as "artificial intelligence," "machine learning," "supply chain resilience," "demand forecasting," "inventory optimization," "COVID-19," and "generative AI" across academic databases and publisher platforms, consistent with search strategies reported in prior systematic reviews of this literature (Samuels, 2024; Smyth & Dennehy, 2024). The review prioritized peer-reviewed journal articles and conference papers published between 2019 and 2026, supplemented by a small number of foundational pre-2019 works that established the theoretical vocabulary of supply chain resilience (e.g., Christopher & Peck, 2004; Sheffi & Rice, 2005; Ponomarov & Holcomb, 2009) and by recent industry and preprint sources capturing fast-moving developments in generative AI that have not yet been fully absorbed into the peer-reviewed literature (e.g., Jackson et al., 2024; Aghaei et al., 2025).

Sources were organized thematically rather than strictly chronologically, following the structure recommended for narrative reviews of fragmented, multi-disciplinary literatures (Zamani et al., 2023). Seven themes were used to structure the synthesis: AI in supply chain management broadly; supply chain resilience as a theoretical construct; AI-based demand forecasting; AI-based inventory optimization; AI's role during COVID-19 and related disruptions; the benefits reported from AI adoption; and the challenges and limitations that constrain adoption. This thematic structure mirrors the approach used in recent systematic reviews of AI and supply chain resilience (Naz et al., 2022; Samuels, 2024) and allows the review to move from broad context to the two focal capabilities—forecasting and inventory optimization—before evaluating the cross-cutting evidence on benefits, barriers, and gaps that motivates the conceptual framework developed in Section 4.

## III. Literature Review

### 3.1 AI in Supply Chain Management

Artificial intelligence has been progressively integrated into supply chain management as organizations have sought to convert the large volumes of data generated by enterprise resource planning (ERP), point-of-sale, and Internet of Things (IoT) systems into operational advantage. Systematic reviews of this literature describe AI as transforming supply chain management by optimizing procedures, improving decision-making, and enhancing overall efficiency, with applications spanning precise demand prediction, efficient inventory control, and end-to-end transparency (Samuels, 2024). A recent systematic review examining the evolution of AI in supply chains from Industry 4.0 toward Industry 5.0 and 6.0 paradigms found that AI integration significantly improves supply chain management by strengthening demand forecasting, inventory management, and broader decision-making capabilities, while also promoting more human-centric collaboration and sustainability-oriented practice (Samuels, 2024).

A parallel stream of research has examined AI applications in supply chain risk management specifically. Baryannis, Validi, Dani, and Antoniou (2019) provided an early and influential review of AI methods—including machine learning, fuzzy logic, and Bayesian approaches—applied to the identification, assessment, and mitigation of supply chain risk, noting that AI's capacity to process heterogeneous and unstructured data gives it a distinct advantage over traditional risk-management techniques. Building on this foundation, subsequent reviews have catalogued AI applications across supply chain risk assessment

(Nimmy, Hussain, Chakrabortty, Hussain, & Saberi, 2022) and have used bibliometric methods to map the rapid growth of this sub-field since 2020 (Ni, Xiao, & Lim, 2020).

Most recently, the literature has begun to examine generative AI and large language models (LLMs) as a distinct and fast-growing category of AI application in supply chain management. A systematic review following PRISMA guidelines found a sharp increase in LLM-related supply chain publications beginning in 2023, with LLM capabilities evolving from basic natural-language tool use toward more cognitive functions such as multi-turn dialogue and retrieval-augmented reasoning across supply chain tasks (systematic review reported in the International Journal of Production Research, 2026). Jackson et al. (2024) proposed a capability-based framework for analyzing and implementing generative AI across supply chain and operations management, while related work has explored the use of LLMs to automate simulation modelling of logistics systems (Jackson, Saenz, et al., 2024) and to support supply chain risk management through natural-language interfaces (LLM-based risk management framework, IEEE CAI, 2024). Industry deployments illustrate the trend: Microsoft has reported using an LLM-based system to manage hardware supply for its global data centers, reducing decision-making time from days to minutes (Harvard Business Review, as reported in EBSCO Research summary, 2025), while a November 2024 executive survey found that 75 percent of surveyed companies had at least one broad or limited generative-AI implementation within their supply chain functions (Supply Chain Dive, 2025).

### 3.2 Supply Chain Resilience

Supply chain resilience is among the most extensively theorized constructs in operations and supply chain management, yet the literature has historically lacked a single, universally accepted definition (Tukamuhabwa, Stevenson, Busby, & Zorzini, 2015). The construct originates with Christopher and Peck (2004), who defined resilience as the ability of a system to return to its original, or a more desirable, state after being disrupted, and who identified four underlying principles for building resilient supply chains: supply chain re-engineering, collaboration among supply chain partners, agility, and a supply-chain-wide culture of risk management. Christopher and Peck (2004) further decomposed agility into visibility—the ability to see through the entire supply chain—and velocity, the pace at which the supply chain can adapt.

Ponomarov and Holcomb (2009) extended this foundational work by conceptualizing resilience as a multidimensional, adaptive capability embedded in supply chain processes and relationships rather than a single operational attribute, emphasizing that resilient capabilities can and should be developed proactively, before a disruption occurs, rather than purely as a reactive response. Sheffi and Rice (2005) similarly framed resilience in terms of an organization's ability both to resist disruption and to recover rapidly once disrupted, a framing echoed in Pettit, Croxton, and Fiksel's (2013) capability-based assessment tool, which enumerates specific capabilities—including flexibility, redundancy, visibility, and collaboration—that firms can develop to counteract supply chain vulnerabilities. Wieland and Wallenburg (2013) added a relational perspective, distinguishing between proactive agility and reactive robustness as the two principal resilience responses to disturbance, while Kamalahmadi and Mellat-Parast (2016) synthesized this literature into a review of the antecedents and principles of enterprise and supply chain resilience.

Since 2020, this theoretical base has been substantially extended by Ivanov and colleagues through the concept of supply chain viability, which broadens resilience to encompass the sustained ability of an intertwined network of supply chains to survive extraordinary, long-duration disruptions such as the COVID-19 pandemic (Ivanov & Dolgui, 2020). This work introduced the notion of the digital supply chain twin—a computerized, data-driven representation of a supply chain's network state that enables real-time visibility and disruption-impact simulation—as a key technological enabler of resilience and viability in the

Industry 4.0 era (Ivanov & Dolgui, 2021). Ivanov and Dolgui (2022) further proposed "stress testing" supply chains as a means of proactively assessing resilience and creating viable ecosystems, extending the resilience literature from a largely retrospective, case-based orientation toward a predictive, simulation-based one. Recent empirical work has continued to refine the antecedents of resilience, for example by showing that the joint effect of supply chain integration and big data analytics capability shapes distinct configurations of resilience outcomes (Jiang, Feng, & Huang, 2024).

### 3.3 AI-Based Demand Forecasting

Demand forecasting has long been recognized as a foundational planning activity in supply chain management, and it is one of the AI application areas with the deepest empirical evidence base. Traditional statistical approaches such as seasonal ARIMA models have historically dominated retail and manufacturing demand forecasting owing to their maturity and interpretability (comparative time-series review discussed in Retail Demand Forecasting literature, 2023), but a substantial body of research published since 2020 documents a clear shift toward machine learning and deep learning approaches. Huber and Stuckenschmidt (2020) developed a machine learning approach to daily retail demand forecasting that explicitly incorporated calendric special days such as holidays and promotions, demonstrating meaningful accuracy improvements over classical benchmarks. Comparative studies have reinforced this pattern: Mitra et al. (2022) compared five machine learning regression techniques—including random forests, extreme gradient boosting (XGBoost), gradient boosting, adaptive boosting, and artificial neural networks—for a multi-channel retail company and found that hybrid ensemble models combining several of these techniques outperformed any single method.

Deep learning architectures have received particular attention for their ability to model complex, nonlinear demand patterns. Comparative evaluations of tree-based ensembles against long short-term memory (LSTM) networks have found that ensemble tree methods can outperform LSTM models on certain perishable-product categories, with the performance gap varying by product type and data availability (comparative ensemble-versus-LSTM study, 2023). Other studies have enriched demand forecasting models with external data sources: Qureshi et al. (2024) incorporated weather data into a deep learning demand forecasting model for supply chain management, while related work has used social media and internet big-data signals to improve forecast responsiveness to shifting consumer sentiment (social media big data demand forecasting studies, 2023–2024). Khan et al. (2020) demonstrated that combining business intelligence tools with machine learning produced more effective demand forecasts than either approach in isolation, and subsequent studies have extended machine learning demand forecasting into manufacturing (Krishnamoorthy et al., 2024) and food-service contexts (Aci & Yergök, 2023).

The practical stakes of forecasting accuracy are directly connected to inventory outcomes. Improved demand forecasts have been shown to reduce the likelihood of stockouts by enabling more precise inventory optimization (machine learning stockout prediction literature, 2025), and industry case evidence—such as the Otto Group's reported 80 percent reduction in stockout rate following the deployment of predictive machine learning—illustrates the magnitude of potential gains (Oosthuizen et al., 2021, as cited in stockout-prediction literature, 2025). At the same time, several authors caution that forecasting method complexity does not guarantee superior performance in all settings; results from major forecasting competitions indicate that simpler, more frugal models can match or outperform complex machine learning methods for certain retail contexts, particularly where data histories are short or intermittent (Petropoulos, Grushka-Cockayne, Siemsen, & Spiliotis, 2022). This nuance is reinforced by research specifically addressing intermittent demand—a common characteristic of spare parts and slow-moving inventory—which requires forecasting methods tailored to sporadic, non-continuous demand patterns rather than the continuous-demand assumptions underlying many mainstream machine learning models (Boylan & Syntetos, 2021).

### 3.4 AI-Based Inventory Optimization

Inventory optimization represents the second major AI application domain examined in this review, and it is closely coupled to demand forecasting: because inventory decisions are downstream of demand estimates, forecast quality directly conditions the achievable performance of any inventory optimization system (He, Zhang, & Ren, 2021). Systematic reviews of AI in inventory management report substantial growth in this literature since 2012, with the number of published studies accelerating markedly after 2018 as machine learning and reinforcement learning techniques became computationally tractable for realistic, multi-product inventory problems (systematic review of AI applications in inventory management, Archives of Computational Methods in Engineering, 2023).

Reinforcement learning (RL) has emerged as a particularly active research direction. Wang, Peng, and Yang (2022) applied deep reinforcement learning to classical inventory management problems, demonstrating that RL agents can learn near-optimal replenishment policies without requiring the restrictive distributional assumptions of classical inventory theory. Meisheri et al. (2022) extended this line of work to scalable, multi-product inventory control under lead-time constraints, addressing one of the central computational challenges that has historically limited the applicability of exact optimization methods to real-world, large-assortment inventory systems. Domain-specific applications have further demonstrated the versatility of AI-based inventory optimization: Abu Zwaida, Pham, and Beauregard (2021) applied optimization techniques to prevent drug shortages in hospital supply chains, illustrating the life-critical stakes of inventory decisions in healthcare contexts, while other studies have applied deep reinforcement learning to the inventory control of multiple perishable goods with an explicit sustainability objective (perishable-goods reinforcement learning literature, Sustainable Energy Technologies and Assessments, 2021).

Beyond reinforcement learning, prescriptive analytics—which combines predictive modeling with optimization to recommend specific replenishment actions—has been applied to inventory management in contexts ranging from health systems to e-commerce (prescriptive analytics for inventory management in health, 2021). In e-commerce and retail settings specifically, AI-driven optimization models have been used to jointly address demand prediction, inventory positioning, and delivery-time reduction under cost constraints (Kaul & Khurana, 2022), while sector-specific studies in automotive and consumer retail supply chains have documented reductions in excess inventory and stockout costs following AI adoption (automotive AI inventory management literature, 2024; AI-driven inventory management in retail supermarkets, 2025). Collectively, this literature indicates that AI-based inventory optimization functions as a critical translation mechanism, converting improved demand visibility into concrete reductions in both understocking and overstocking risk—two failure modes that are directly implicated in supply chain resilience, since excessive safety stock ties up working capital while insufficient stock undermines the ability to absorb demand shocks (Dey et al., 2024).

### 3.5 AI during COVID-19 and Supply Chain Disruptions

The COVID-19 pandemic served as an inflection point for research on AI and supply chain resilience, generating a distinct and rapidly growing sub-literature. Ivanov (2020) provided one of the earliest and most widely cited analyses, using simulation-based modeling to predict the impact of the coronavirus outbreak on global supply chains and to quantify both the short-term and long-term consequences of epidemic-driven disruption. This work catalyzed a broader research agenda on supply chain viability, formalized in Ivanov and Dolgui's (2020) position paper, which argued that the scale and duration of the COVID-19 disruption required extending resilience thinking toward the survivability of entire intertwined supply networks rather than single firms or dyadic relationships.

A number of studies examined how AI and digital technologies were specifically mobilized during the pandemic to sustain supply chain operations. Dubey, Bryde, Blome, Roubaud, and Giannakis (2021) examined how AI-powered supply chain analytics were facilitated through inter-organizational alliance management during the pandemic crisis in business-to-business contexts, finding that firms with stronger analytics-enabled alliances were better positioned to maintain visibility and coordination under crisis conditions. Burgos and Ivanov (2021) applied a digital-twin-based impact analysis to food retail supply chains during COVID-19, demonstrating how simulation and AI-enabled visibility tools could be used to model pandemic-driven demand shocks and identify improvement directions for retail resilience. Kähkönen, Evangelista, Hallikas, Immonen, and Lintukangas (2021) examined COVID-19 as a trigger for dynamic capability development, arguing that the pandemic accelerated organizational learning around resilience-building capabilities, including digital and analytical ones.

Naz, Kumar, Majumdar, and Agrawal (2022) conducted an exploratory, state-of-the-art review directly addressing whether AI functions as an enabler of supply chain resiliency in the post-COVID-19 environment, concluding that while AI shows strong potential across forecasting, risk detection, and disruption response, the empirical evidence linking specific AI capabilities to resilience outcomes remained fragmented and in need of more rigorous, theory-driven research. Related work examined the use of AI and machine learning to detect fake news and disinformation that could otherwise trigger panic-buying-driven supply chain disruptions during the pandemic (Akhtar, Ghouri, Khan et al., 2023), illustrating the breadth of AI applications mobilized in the crisis response beyond core forecasting and inventory functions. More recent work has extended these pandemic-era lessons to specific developing-economy manufacturing contexts, examining how AI-driven capabilities supported supply chain resilience among small and medium-sized manufacturing enterprises in Vietnam in the years following the initial pandemic shock (Dey et al., 2024).

### 3.6 Benefits of AI Adoption

Across the literature reviewed, AI adoption in supply chain management is associated with a consistent set of reported benefits. First, forecast and planning accuracy improvements are the most frequently documented gain: AI-enabled forecasting techniques have been associated with substantial reductions in forecasting error relative to traditional statistical methods, in some cases described in the operations research literature as reductions of up to 50 percent, alongside reported reductions in lost sales of up to 65 percent and reductions in end-to-end supply chain costs of around 25 percent (figures reported in recent operations-research literature on AI-driven supply chains; see also Zhao & Strotmann, 2022, on AI forecasting in automotive supply chains). Second, inventory-related cost and service-level benefits are widely reported, including reduced stockout rates—illustrated by the Otto Group's reported 80 percent stockout-rate reduction following predictive machine learning deployment (Oosthuizen et al., 2021, as cited in recent stockout-prediction research)—and reduced excess inventory and holding costs (Çaylı & Oralhan, 2024).

Third, AI adoption has been linked to faster and more scalable decision-making. Microsoft's deployment of an LLM-based supply chain decision-support system reportedly reduced decision-making time from days to minutes while enabling planners to interact directly with supply chain data without relying on data-science specialists (reported in Harvard Business Review coverage summarized in EBSCO Research, 2025). Similarly, Unilever's use of generative AI and LLM-based tools for sales, market, and weather forecasting across global locations has been associated with roughly a 30 percent reduction in supply chain planning errors, while Maersk's use of generative AI for automated supplier contracting has been reported to cut manual contract-review time by approximately 50 percent (industry case examples summarized in Yanamandra, 2025). Fourth, AI has been credited with strengthening specific resilience-relevant capabilities directly, including visibility (through digital supply chain twins; Ivanov & Dolgui, 2021), risk detection (through AI-enabled supply chain risk management systems; Baryannis et al., 2019), and disruption-impact simulation (through digital twin and stress-testing approaches; Ivanov & Dolgui, 2022).

### 3.7 Challenges and Limitations

Despite these benefits, the literature identifies a consistent set of challenges that constrain AI adoption in supply chain contexts. Data quality and integration issues are the most frequently cited barrier: AI models depend on large volumes of accurate, well-structured, real-time data, and incomplete, inconsistent, or siloed data across fragmented supply chain stakeholders has been repeatedly identified as undermining model performance and organizational trust in AI outputs (data-quality challenges in AI-enabled logistics literature, 2025; drivers, barriers, and social considerations for AI adoption in SCM literature, 2023). Cost is a related and equally persistent barrier: the computing infrastructure, cloud storage, and continuous model retraining that AI systems require impose substantial upfront costs that fall disproportionately on small and medium-sized enterprises, contributing to uneven adoption across firm size (Haleem et al., 2023, as cited in AI logistics optimization literature, 2025).

A second major barrier is the limited explainability, or "black-box" nature, of many AI models, particularly deep learning and ensemble-based methods. Surveys of enterprise technology leaders have found that a lack of explainability is among the most commonly cited barriers to scaling AI projects across organizations, with IBM's 2023 Global AI Adoption Index reporting that over half of enterprise IT leaders identified explainability gaps as a critical constraint (IBM, 2023, as cited in black-box AI literature, 2025). Within supply chain management specifically, this problem is amplified because planning and demand decisions typically require human-in-the-loop review and cross-functional communication across finance, operations, and supplier-facing teams; when planners cannot understand why a model recommends a counterintuitive action—such as sharply reducing safety stock for a top-selling item—trust in the recommendation, and therefore adoption, suffers (barriers to AI implementation in supply chain management literature, 2024; Olan, Spanaki, Ahmed, & Zhao, 2024, on enabling explainable AI capabilities in supply chain decision support). Recent supply chain-specific evidence reinforces this pattern: in a large-scale retail deployment, the limited interpretability of black-box machine learning algorithms was identified as a significant adoption barrier among operational planning teams, even as those same models delivered measurable accuracy gains (AI supply chain intelligence case study, 2026).

Third, organizational and workforce-related barriers recur throughout the literature. Cultural resistance to AI, driven partly by fear of job displacement among operational staff, has been found to slow the organizational change processes and cross-functional collaboration that successful AI implementation requires (barriers to AI adoption in supply chain management, industry-leader perspectives, 2025). A 2026 roadmap on AI and machine learning in smart manufacturing similarly identifies workforce skills gaps, reluctance to adopt technologies perceived as threatening job security, data quality and integration challenges, model explainability, potential algorithmic bias, and governance arrangements for highly distributed systems as the principal current and future challenges to AI adoption in supply chains (AI/ML smart manufacturing roadmap, 2026). Finally, several reviews note a more fundamental research and evidentiary gap: much of the existing empirical literature remains fragmented across disconnected technology types, industry contexts, and disciplinary traditions, limiting the ability of both researchers and practitioners to draw generalizable conclusions about which AI capabilities most reliably strengthen resilience, under which conditions, and over what time horizon (Smyth & Dennehy, 2024; Naz et al., 2022).

## IV. Discussion, Research Gaps, and Conceptual Framework

### 4.1 Discussion

The literature reviewed in Section 3 converges on a broadly consistent narrative: AI-based demand forecasting improves the accuracy and granularity of demand signals; AI-based inventory optimization translates those improved signals into more precise replenishment decisions; and, together, these two capabilities are theorized to strengthen the visibility, agility, and viability dimensions of supply chain resilience identified in the foundational resilience literature (Christopher & Peck, 2004; Ponomarov & Holcomb, 2009; Ivanov & Dolgui, 2021). The COVID-19 pandemic functioned as both a stress test and an accelerant for this relationship: pandemic-era studies demonstrate that firms and networks with stronger AI-enabled analytics, digital-twin-based visibility, and alliance-based data sharing were better positioned to sense and respond to demand and supply shocks (Dubey et al., 2021; Burgos & Ivanov, 2021; Kähkönen et al., 2021), even as reviewers caution that the evidence remains largely descriptive and case-based rather than causally established (Naz et al., 2022).

At the same time, the discussion of benefits and challenges in Sections 3.6 and 3.7 suggests that the relationship between AI adoption and resilience is not unconditional. The magnitude of reported benefits—accuracy gains of up to 50 percent, cost reductions of around 25 percent, stockout reductions of up to 80 percent in specific cases—coexists with a persistent set of adoption barriers around data quality, explainability, cost, and workforce readiness that are unevenly distributed across firms, with small and medium-sized enterprises facing disproportionate constraints (Haleem et al., 2023; Dey et al., 2024). This suggests that AI's contribution to resilience is likely to be moderated by organizational and contextual factors—including data infrastructure maturity, firm size, and workforce capability—that are not yet well specified in the existing literature.

### 4.2 Research Gaps

Synthesizing across the seven thematic areas reviewed, four principal research gaps can be identified. First, there is a measurement and causality gap: although AI-based forecasting and inventory optimization are frequently associated with resilience-relevant outcomes in the literature, few studies directly and quantitatively link specific AI capabilities to validated, multidimensional resilience metrics (e.g., time-to-recovery, service-level maintenance during disruption) rather than to efficiency or accuracy metrics alone (Zamani et al., 2023; Naz et al., 2022). Second, there is a context and generalizability gap: much of the COVID-19-era evidence is drawn from large firms, specific sectors such as retail, food, and manufacturing, or single-country settings, leaving open questions about how AI-enabled resilience capabilities transfer to small and medium-sized enterprises, developing-economy contexts, and non-pandemic disruption types such as cyberattacks or geopolitical shocks (Dey et al., 2024).

Third, there is an explainability and human-integration gap: while the technical literature on explainable AI (XAI) is growing, comparatively little supply chain-specific research examines how planners' trust in, and effective use of, AI recommendations can be systematically built, or how human-AI collaborative decision-making should be designed in high-stakes planning contexts (Olan et al., 2024; Nimmy et al., 2022). Fourth, there is an emerging-technology gap specific to generative AI and LLMs: because most peer-reviewed empirical work on generative AI in supply chains has appeared only since 2023–2024, rigorous, replicated evidence on the resilience implications of LLM-based decision support—as distinct from its efficiency and productivity implications—remains scarce, even as industry adoption accelerates rapidly (Jackson et al., 2024; Supply Chain Dive, 2025).

### 4.3 Conceptual Framework

Building on the literature review and the research gaps identified above, this paper proposes a conceptual framework linking AI-Enabled Forecasting Capability and AI-Enabled Inventory Optimization Capability, as joint independent variables, to Supply Chain Resilience, as the dependent variable, with Data and Organizational Readiness (encompassing data quality/integration, explainability practices, and workforce capability) proposed as a moderating condition. Table 1 summarizes the constructs.

| Construct | Description / Indicators |
|---|---|
| AI-Based Demand Forecasting Capability | Use of machine learning / deep learning methods (e.g., gradient boosting, LSTM, ensemble models) to generate demand signals; forecast accuracy (e.g., reduced MAPE); incorporation of external signals (weather, social sentiment, promotions) |
| AI-Based Inventory Optimization Capability | Use of reinforcement learning / prescriptive analytics to set replenishment policies, safety stock, and reorder points; stockout rate; excess inventory / holding cost |
| Data and Organizational Readiness (Moderator) | Data quality and integration across supply chain tiers; explainability / trust-building practices; workforce AI literacy and change-management capacity |
| Supply Chain Resilience (Dependent Variable) | Visibility, agility, redundancy, and collaboration capabilities (Christopher & Peck, 2004; Pettit et al., 2013); disruption absorption and recovery speed; viability under sustained, network-level disruption (Ivanov & Dolgui, 2020) |

*Table 1. Constructs of the proposed conceptual framework.*

**AI-Based Demand Forecasting Capability**

▼

**AI-Based Inventory Optimization Capability**

▼ ◄— moderated by: Data & Organizational Readiness

**Supply Chain Resilience (Visibility · Agility · Redundancy · Collaboration · Viability)**

*Figure 1. Conceptual model linking AI-based demand forecasting and inventory optimization to supply chain resilience, moderated by data and organizational readiness.*

The framework proposes that AI-based demand forecasting capability directly strengthens inventory optimization capability, since accurate demand signals are a necessary input to effective replenishment decisions (He, Zhang, & Ren, 2021), and that both capabilities jointly contribute to supply chain resilience through their effects on visibility (via improved demand and inventory transparency), agility (via faster, more automated replenishment decisions), and redundancy (via more precisely calibrated, rather than uniformly high, safety-stock buffers). The strength of this relationship is proposed to be moderated by data and organizational readiness: where data quality is poor, explainability practices are weak, or workforce trust in AI is low, the theoretical benefits of AI-based forecasting and inventory optimization are unlikely to be fully realized in practice—consistent with the adoption-barrier evidence reviewed in Section 3.7 (Olan et al., 2024; Haleem et al., 2023).

## V. Conclusion

This paper has reviewed the literature on artificial intelligence and supply chain resilience, with particular emphasis on two of the most mature and consequential AI application domains: demand forecasting and inventory optimization. The review indicates that AI—spanning classical machine learning, deep learning, reinforcement learning, and, increasingly, generative AI and large language models—has been widely adopted across supply chain functions, with demand forecasting and inventory optimization functioning as foundational and closely coupled capabilities. Machine learning-based forecasting methods have been repeatedly shown to outperform traditional statistical approaches in retail, manufacturing, and food-service contexts (Huber & Stuckenschmidt, 2020; Mitra et al., 2022), while reinforcement learning and prescriptive analytics have extended inventory optimization to complex, multi-product, multi-echelon problems that were previously computationally intractable (Wang, Peng, & Yang, 2022; Meisheri et al., 2022).

The COVID-19 pandemic served as a critical proving ground for this literature, generating an influential body of research—much of it associated with Ivanov and colleagues—that reframed supply chain resilience in terms of network-level viability and demonstrated the value of AI-enabled digital supply chain twins, alliance-based analytics, and simulation-based stress testing during a sustained, large-scale disruption (Ivanov, 2020; Ivanov & Dolgui, 2020, 2021, 2022; Dubey et al., 2021; Burgos & Ivanov, 2021). The benefits documented across this literature are substantial and consistent: improved forecast accuracy, reduced stockouts and excess inventory, faster decision cycles, and strengthened visibility and risk-detection capabilities (Baryannis et al., 2019; Yanamandra, 2025). These benefits, however, are conditioned by a persistent set of adoption barriers, most notably data quality and integration challenges, the limited explainability of many AI models, high implementation costs that disproportionately burden smaller firms, and organizational resistance rooted in workforce concerns about job displacement (Olan et al., 2024; IBM, 2023; Haleem et al., 2023).

Taken together, these findings support the paper's central contention: AI-based demand forecasting and inventory optimization are best understood not as resilience mechanisms in their own right, but as capabilities whose contribution to resilience is conditional on the surrounding data infrastructure, explainability practices, and organizational readiness of the adopting firm. The conceptual framework developed in Section 4.3 formalizes this contention, positioning demand forecasting and inventory optimization as linked, resilience-relevant capabilities whose effects are moderated by data and organizational readiness. This framing helps reconcile two strands of evidence that might otherwise appear contradictory: the striking efficiency and accuracy gains reported across case studies and industry deployments, and the persistent caution expressed by systematic reviewers regarding the fragmented and largely non-causal nature of the existing evidence base (Naz et al., 2022; Smyth & Dennehy, 2024; Zamani et al., 2023).

For practitioners, the review suggests that organizations seeking to leverage AI for supply chain resilience should treat demand forecasting and inventory optimization as an integrated capability rather than as separate technology investments, and should invest concurrently in the data infrastructure, explainability tooling, and workforce change-management processes that determine whether AI-generated recommendations are trusted and acted upon. For researchers, the review points toward four priority directions: developing and validating resilience-specific (rather than purely efficiency-specific) metrics for evaluating AI impact; extending the evidence base beyond large firms and pandemic-era disruptions to small and medium-sized enterprises and to non-pandemic disruption types; developing supply chain-specific frameworks for human-AI collaborative decision-making under explainability constraints; and generating rigorous, replicated evidence on the resilience implications of generative AI and LLM-based decision support, a technology category whose adoption is currently outpacing the empirical literature evaluating its effects. As supply chains continue to operate in an environment of sustained volatility, closing these gaps will be essential to converting AI's demonstrated technical potential into reliably resilient supply chain outcomes.

## References

[1] Abu Zwaida, T., Pham, C., & Beauregard, Y. (2021). Optimization of inventory management to prevent drug shortages in the hospital supply chain. Applied Sciences, 11(6), 2726.

[2] Aci, M., & Yergök, D. (2023). Demand forecasting for food production using machine learning algorithms: A case study of university refectory. Tehnički Vjesnik, 30(6). https://doi.org/10.17559/TV-20230117000232

[3] Aghaei, R., Kiaei, A. A., Boush, M., Vahidi, J., Barzegar, Z., & Rofoosheh, M. (2025). The potential of large language models in supply chain management: Advancing decision-making, efficiency, and innovation. arXiv preprint arXiv:2501.15411.

[4] Akhtar, P., Ghouri, A. M., Khan, H. U. R., Amin ul Haq, M., Awan, U., Zahoor, N., Khan, Z., & Ashraf, A. (2023). Detecting fake news and disinformation using artificial intelligence and machine learning to avoid supply chain disruptions. Annals of Operations Research, 327, 633–657.

[5] Baryannis, G., Validi, S., Dani, S., & Antoniou, G. (2019). Supply chain risk management and artificial intelligence: A review of the state of the art. International Journal of Production Research, 57(7), 2179–2202.

[6] Boylan, J. E., & Syntetos, A. A. (2021). Intermittent demand forecasting: Context, methods and applications. John Wiley & Sons.

[7] Burgos, D., & Ivanov, D. (2021). Food retail supply chain resilience and the COVID-19 pandemic: A digital twin-based impact analysis and improvement directions. Transportation Research Part E: Logistics and Transportation Review, 152, 102412.

[8] Christopher, M., & Peck, H. (2004). Building the resilient supply chain. International Journal of Logistics Management, 15(2), 1–14.

[9] Çaylı, O., & Oralhan, Z. (2024). Artificial intelligence-driven inventory management: Optimizing stock levels and reducing costs through advanced machine learning techniques. European Journal of Research and Development, 4(4).

[10] Dey, P. K., Chowdhury, S., Abadie, A., Vann Yaroson, E., & Sarkar, S. (2024). Artificial intelligence-driven supply chain resilience in Vietnamese manufacturing small-and-medium-sized enterprises. International Journal of Production Research, 62(15), 5417–5456.

[11] Dolgui, A., & Ivanov, D. (2021). Ripple effect and supply chain disruption management: New trends and research directions. International Journal of Production Research, 59(1), 102–109.

[12] Dubey, R., Bryde, D. J., Blome, C., Roubaud, D., & Giannakis, M. (2021). Facilitating artificial intelligence powered supply chain analytics through alliance management during the pandemic crises in the B2B context. Industrial Marketing Management, 96, 135–146.

[13] He, Y., Zhang, M., & Ren, S. (2021). Artificial intelligence in inventory management: A review and future research agenda. International Journal of Production Research, 59(7), 2108–2126.

[14] Huber, J., & Stuckenschmidt, H. (2020). Daily retail demand forecasting using machine learning with emphasis on calendric special days. International Journal of Forecasting, 36(4), 1420–1438.

[15] IBM. (2023). Global AI Adoption Index 2023. IBM Corporation.

[16] Ivanov, D. (2020). Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. Transportation Research Part E: Logistics and Transportation Review, 136, 101922.

[17] Ivanov, D., & Dolgui, A. (2020). Viability of intertwined supply networks: Extending the supply chain resilience angles towards survivability. A position paper motivated by COVID-19 outbreak. International Journal of Production Research, 58(10), 2904–2915.

[18] Ivanov, D., & Dolgui, A. (2021). A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. Production Planning & Control, 32(9), 775–788.

[19] Ivanov, D., & Dolgui, A. (2022). Stress testing supply chains and creating viable ecosystems. Operations Management Research, 15, 475–486.

[20] Jackson, I., Ivanov, D., Dolgui, A., & Werner, F. (2024). Generative artificial intelligence in supply chain and operations management: A capability-based framework for analysis and implementation. International Journal of Production Research, 62, 6120–6145.

[21] Jackson, I., Saenz, M. J., Ivanov, D., & Wang, J. (2024). From natural language to simulations: Applying AI to automate simulation modelling of logistics systems. International Journal of Production Research, 62(4), 1434–1457.

[22] Jiang, Y., Feng, T., & Huang, Y. (2024). Antecedent configurations toward supply chain resilience: The joint impact of supply chain integration and big data analytics capability. Journal of Operations Management.

[23] Kähkönen, A.-K., Evangelista, P., Hallikas, J., Immonen, M., & Lintukangas, K. (2021). COVID-19 as a trigger for dynamic capability development and supply chain resilience improvement. International Journal of Production Research.

[24] Kamalahmadi, M., & Mellat-Parast, M. (2016). A review of the literature on the principles of enterprise and supply chain resilience: Major findings and directions for future research. International Journal of Production Economics, 171, 116–133.

[25] Kaul, D., & Khurana, R. (2022). AI-driven optimization models for e-commerce supply chain operations: Demand prediction, inventory management, and delivery time reduction with cost efficiency considerations. International Journal of Social Analytics, 7(12), 59–77.

[26] Khan, M. A., Saqib, S., Alyas, T., Ur Rehman, A., Saeed, Y., Zeb, A., Zareei, M., & Mohamed, E. M. (2020). Effective demand forecasting model using business intelligence empowered with machine learning. IEEE Access, 8, 116013–116023.

[27] Krishnamoorthy, K., et al. (2024). Machine learning for demand forecasting in manufacturing. International Journal for Multidisciplinary Research, 6(1).

[28] Meisheri, H., Sultana, N. N., Baranwal, M., Baniwal, V., Nath, S., Verma, S., Ravindran, B., & Khadilkar, H. (2022). Scalable multi-product inventory control with lead time constraints using reinforcement learning. Neural Computing and Applications, 34(3), 1735–1757.

[29] Mitra, A., et al. (2022). A comparative study of demand forecasting models for a multi-channel retail company. Operations Research Forum, 3(58).

[30] Naz, F., Kumar, A., Majumdar, A., & Agrawal, R. (2022). Is artificial intelligence an enabler of supply chain resiliency post COVID-19? An exploratory state-of-the-art review for future research. Operations Management Research, 15(1), 378–398.

[31] Nimmy, S. F., Hussain, O. K., Chakrabortty, R. K., Hussain, F. K., & Saberi, M. (2022). Explainability in supply chain operational risk management: A systematic literature review. Knowledge-Based Systems, 235, 107587.

[32] Ni, D., Xiao, Z., & Lim, M. K. (2020). A systematic review of the research trends of machine learning in supply chain management. International Journal of Machine Learning and Cybernetics, 11(7), 1463–1482.

[33] Olan, F., Spanaki, K., Ahmed, W., & Zhao, G. (2024). Enabling explainable artificial intelligence capabilities in supply chain decision support making. Production Planning & Control.

[34] Petropoulos, F., Grushka-Cockayne, Y., Siemsen, E., & Spiliotis, E. (2022). Wielding Occam's razor: Fast and frugal retail forecasting (Working paper). University of Bath / University of Virginia / University of Wisconsin.

[35] Pettit, T. J., Croxton, K. L., & Fiksel, J. (2013). Ensuring supply chain resilience: Development and implementation of an assessment tool. Journal of Business Logistics, 34(1), 46–76.

[36] Ponomarov, S. Y., & Holcomb, M. C. (2009). Understanding the concept of supply chain resilience. International Journal of Logistics Management, 20(1), 124–143.

[37] Qureshi, N. U. H., et al. (2024). Demand forecasting in supply chain management using weather enhanced deep learning model. IEEE Access, 12, 145570–145581.

[38] Samuels, A. (2024). Examining the integration of artificial intelligence in supply chain management from Industry 4.0 to 6.0: A systematic literature review. Frontiers in Artificial Intelligence, 7, 1477044.

[39] Sheffi, Y., & Rice, J. B. (2005). A supply chain view of the resilient enterprise. MIT Sloan Management Review, 47(1), 41–48.

[40] Simchi-Levi, D., Mellou, K., Menache, I., & Pathuri, J. (2026). Large language models for supply chain decisions. In M. C. Cohen & T. Dai (Eds.), AI in supply chains: Perspectives from global thought leaders (Springer Series in Supply Chain Management, Vol. 27, pp. 93–104). Springer.

[41] Smyth, C., & Dennehy, D. (2024). Artificial intelligence and prescriptive analytics for supply chain resilience: A systematic literature review and research agenda. International Journal of Production Research, 62, 8537–8561.

[42] Supply Chain Dive. (2025, August 22). Logistics management is leveling up with generative AI. Supply Chain Dive.

[43] Tukamuhabwa, B. R., Stevenson, M., Busby, J., & Zorzini, M. (2015). Supply chain resilience: Definition, review and theoretical foundations for further study. International Journal of Production Research, 53(18), 5592–5623.

[44] Wang, Q., Peng, Y., & Yang, Y. (2022). Solving inventory management problems through deep reinforcement learning. Journal of Systems Science and Systems Engineering, 31(6), 677–689.

[45] Wieland, A., & Wallenburg, C. M. (2013). The influence of relational competencies on supply chain resilience: A relational view. International Journal of Physical Distribution & Logistics Management, 43(4), 300–320.

[46] Yanamandra, R. (2025). Generative AI (large language models) in supply chain management. Hamdan Bin Mohammed Smart University Knowledge Update.

[47] Zamani, E. D., Smyth, C., Gupta, S., & Dennehy, D. (2023). Artificial intelligence and big data analytics for supply chain resilience: A systematic literature review. Annals of Operations Research, 327(2), 605–632.

[48] Zhao, L., & Strotmann, H. (2022). Artificial intelligence for forecasting in automotive industry supply chain management. Operations Management Research, 15(1–2), 34–49.