Economics and Public Policy
ISSN Print: 3104-4387
ISSN Online: 3104-4395
CD ISSN: 3104-4409
https://doi.org/10.63313/EPP.9062

From Forecast Accuracy to Resilience: The Impact of Artificial Intelligence on Supply Chain Management

Zhixian He
School of Economics and Management, Southwest Petroleum University, Chengdu 610500, China
Email: xuekaka@163.com

How to cite this paper: He, Z. (2026). From forecast accuracy to resilience: The impact of artificial intelligence on supply chain management. Economics and Public Policy, 3(2), 61–66. ISSN Print: 3104-4387, ISSN Online: 3104-4395.
https://doi.org/10.63313/EPP.9062
Published: 2026-11-26

Copyright © 2026 by author(s) and Erytis Publishing Limited.
This work is licensed under the Creative Commons Attribution International License (CC BY 4.0).
http://creativecommons.org/licenses/by/4.0/
CC BY 4.0

Abstract

Artificial intelligence (AI) is increasingly presented as a general-purpose technology for supply chain management, yet the literature remains fragmented across technology families, functional areas and research designs. This paper develops an integrative account of how AI changes supply chain decisions and outcomes. Drawing on nine conceptual, empirical and review sources published between 1997 and 2024, it identifies four mechanisms through which AI affects supply chains: richer demand signal extraction and forecasting; automated evaluation and monitoring of suppliers and contracts; dynamic optimisation of inventory, production and logistics decisions; and earlier detection of, and faster response to, disruption. These mechanisms operate along a ladder of delegated authority that runs from descriptive analytics to bounded autonomous decision-making, and their realisation depends on data infrastructure, organisational absorptive capacity and governance rather than on algorithms alone. Reported performance effects are positive but conditional: survey evidence associates AI-enabled analytics with operational and environmental performance, whereas benchmarking evidence shows that machine learning does not automatically outperform established statistical methods. The paper concludes that the principal impact of AI is less the substitution of human planners than the compression of decision latency and the reallocation of managerial attention, and it identifies the data, organisational and governance conditions on which those gains depend.

Keywords

Artificial Intelligence; Supply Chain Management; Demand Forecasting; Supply Chain Resilience; Generative AI; Decision Latency

1. Introduction

Supply chains are decision systems as much as physical networks. Every order and shipment embeds a forecast, a replenishment rule, a supplier choice or a routing

decision, and the quality of these decisions determines cost, service and resilience. The information on which they rest is nevertheless chronically incomplete: demand is distorted as it travels upstream [1], lead times vary, supplier capacity is opaque, and disruptive events arrive faster than periodic planning cycles can absorb. Managers have therefore buffered uncertainty with deterministic rules, safety stock and long review cycles.

Artificial intelligence (AI) is attractive in this setting because it converts heterogeneous data into decisions at a speed and granularity that manual processes cannot match. Min [2] concluded early that expert systems, neural networks, genetic algorithms and fuzzy logic could support supply chain decisions, although adoption remained constrained by data availability and implementation cost. A decade later, bibliometric and systematic reviews document rapid growth concentrated in forecasting, procurement, production planning and logistics [3], while Baryannis et al. [4] map AI onto the tasks of risk identification, assessment and response. The literature nevertheless remains fragmented along two axes: technological, with studies clustering around individual methods, and functional, with forecasting, procurement and logistics papers using different outcomes and different notions of performance. Claims that AI improves supply chain management are therefore often pitched above the level the evidence can support , for instance, Makridakis et al. [5] found that machine learning did not outperform established statistical benchmarks across the M3 series.

This paper asks three questions. Through which mechanisms does AI alter supply chain decisions and, through them, outcomes? Under what organisational and structural conditions do these mechanisms operate? And what does the available evidence actually show? It answers them by synthesising nine conceptual, empirical and review sources published between 1997 and 2024, selected by citation tracing from three anchor reviews and restricted to work concerned with the relation between AI and supply chain decisions, performance or risk. The review is integrative rather than exhaustive: it reconstructs the causal logic that links a technology to a decision and a decision to an outcome, and confronts that logic with what has been reported. Section 2 sets out a taxonomy and an autonomy ladder, Section 3 traces the mechanisms, Section 4 reviews the evidence, Section 5 examines boundary conditions, and Section 6 concludes.

2. AI Technologies and Supply Chain Decisions

AI in supply chain management is not a single technology but a family of computational approaches that differ in what they learn, what data they require and how their outputs can be verified. Table 1 groups the principal families by the computation they perform and by the task they most naturally address. Rule-based and expert systems encode domain knowledge as conditional rules and remain useful where decisions must be auditable and stable, such as supplier qualification

and customs classification. Machine learning, including deep networks for images, documents and speech, extracts patterns from historical and unstructured records and is the workhorse of demand forecasting, lead-time prediction, inspection and supplier risk scoring. Reinforcement learning learns sequential policies through interaction with an environment, which suits inventory control, scheduling and routing, where the consequence of a decision unfolds over time. Generative AI adds a capacity to interpret and produce language, and therefore to support contract analysis, supplier communication and planning assistance [6]. The families differ mainly in verification burden: a demand model can be validated against held-out periods, whereas a generated supplier assessment must be checked against source evidence.

Table 1. A functional taxonomy of AI technologies in supply chain management.

Technology family	Typical supply chain applications	Dominant impact mechanism
Rule-based and expert systems	Supplier qualification, customs classification, exception handling	Codified decision rules; consistency and auditability
Machine learning (including deep learning)	Demand forecasting, lead-time prediction, inspection, supplier risk scoring	Pattern extraction from historical and unstructured data
Reinforcement learning	Inventory control, scheduling, routing, dynamic pricing	Sequential decision optimisation under uncertainty
Generative AI	Contract analysis, supplier communication, planning assistance	Language understanding and synthesis; decision support

Source: compiled by the author from the sources cited in Table 1 [2, 3, 4, 6].

Adoption is commonly described as a progression from descriptive to predictive to prescriptive analytics and finally to autonomy, but it is better read as a gradient of delegated authority: what limits movement up the ladder is rarely model accuracy, but the cost of a wrong action, the availability of a fallback, the traceability of the reasoning and the willingness of an organisation to attach its name to a machine recommendation. Min [2] located AI mainly at the prescriptive stage, as support for planners, and Baryannis et al. [4] show that risk applications have advanced furthest in identification and assessment and least in response, where decisions commit resources and carry accountability.

3. Mechanisms of Impact along the Supply Chain

In each domain below, a data-generating process produces signals, a model converts them into an estimate or recommendation, a decision is taken with or without human approval, and the decision changes a physical or financial flow; the domains differ in feedback latency, cost of error and attributability.

3.1. Demand Forecasting and Planning

Forecasting is the most studied application and the one with the clearest mechanism. Statistical methods extrapolate level, trend and seasonality from a single demand history; machine learning adds covariates such as price, promotion, weather, lead time and customer behaviour, and can learn non-linear interactions across item,

store and channel hierarchies. Where these covariates carry genuine information not already embedded in the history, forecast error falls and the planning system inherits the improvement. Safety stock can then be reduced for a given service level, obsolete inventory and markdowns decline, and the amplification of demand variability upstream is attenuated because each tier plans on a less distorted signal [1]. The mechanism is nonetheless conditional: machine learning does not automatically dominate benchmarks [5], and forecast accuracy is not decision quality, since intermittent and new products offer little history for complex models.

3.2. Procurement and Supplier Management

Procurement is where AI changes the boundary of what can be monitored. Supplier selection has relied on periodic questionnaires, audits and price comparisons; machine learning can combine financial indicators, delivery performance, quality records, news and geopolitical signals into a continuously updated risk score, while language processing extracts obligations, penalties and renewal terms from contracts. Each channel replaces a periodic, sampled process with a continuous one, so the value comes from eliminating blind periods rather than from better prediction. The same capabilities introduce hazards: scores built on historical defaults may reproduce the biases of past sourcing decisions, and summarisation can omit a qualification that changes the meaning of an obligation, so a documented review path is needed wherever the recommendation contributes to a decision with legal consequences.

3.3. Production, Logistics and Risk Response

In production and inventory, AI shifts planning from fixed parameters to continuously revised estimates: demand-driven replenishment recalculates reorder points as distributions change, reinforcement learning trades off changeover cost and due-date performance across a sequence of dispatch decisions, and condition monitoring turns maintenance from a calendar activity into a condition-triggered one. In logistics, short feedback cycles favour learning, and route optimisation, load building and dynamic carrier selection produce value through real-time re-optimisation rather than prediction. Risk management is where the conceptual promise is largest and the record thinnest. Baryannis et al. [4] show that AI methods span identification, assessment and response, but response decisions commit resources and are rarely tested against realised disruption performance. Generative models can draft scenario narratives and assemble playbooks, shortening the interval between detection and response [6], yet generated content is plausible rather than verified, so its value depends on verification against authoritative records.

4. Evidence on Performance Outcomes

Survey evidence provides the clearest association between AI-enabled analytics and performance. Dubey et al. [7], using responses from 256 manufacturing firms in India, find a positive association with operational performance that is contingent on entrepreneurial orientation and environmental dynamism. Benzidia et al. [8], studying 168 French hospitals with structural equation modelling, find that big data analytics and AI improve environmental process integration and green collaboration, and that both subsequently improve environmental performance: emissions, energy and waste become visible at the process level, which allows joint action with suppliers and customers. Sanders et al. [9] treat such findings as an agenda rather than a conclusion, since data quality, metric design and boundary-spanning collaboration remain unresolved.

Two qualifications follow. First, the dominant designs are cross-sectional surveys and reviews, which establish association rather than causation and are vulnerable to reverse causality, because better-performing firms may simply be able to afford analytics. Second, outcome variables differ across studies, so gains in forecast accuracy, operational performance and environmental performance cannot be aggregated into a single effect. Benchmark evidence supplies a corrective: if learned forecasting models can be less accurate and more costly than established methods [5], the value of AI is realised at the level of the decision system, where data, model, policy and oversight are jointly configured, and isolating the model is the wrong unit of evaluation.

5. Boundary Conditions and Unintended Effects

Data quality is the first constraint. Supply chain records are produced by different firms under different conventions, and item identities, units and lead times are often inconsistent across systems, so a model can learn artefacts of the recording process. Integration is the second: applications require data held in enterprise resource planning, transport and warehouse management and external sources, and where these are unconnected each application becomes a separate data project whose cost overwhelms the value of the model, which is one reason why large firms with integrated systems capture disproportionate gains.

Organisational capability is the third. A forecast is valuable only if planners trust it enough to change an order, and trust is built through visible validation and a period of parallel running; AI also reallocates labour, reducing routine reporting while increasing exception handling and model supervision. Algorithmic risk is the fourth: models trained on historical data fail when demand patterns, supplier networks or trade conditions shift, so performance that is stable in backtests can decay in deployment. Finally, benefits depend on data volume, integration capacity and specialist skills, which favour large firms and focal buyers, so visibility often stops at tier one, where disruption tends to originate.

6. Conclusion

The impact of AI on supply chain management is best understood as a set of mechanisms rather than a general effect. AI improves the extraction of demand signals, the evaluation of suppliers and contracts, the optimisation of inventory, production and logistics, and the speed of disruption response, and how far these mechanisms deliver depends on data integration, organisational capability and governance rather than on model performance alone. The evidence supports a qualified conclusion: surveys associate AI-enabled analytics with operational and environmental performance and conceptual work establishes the feasibility of digital resilience, yet benchmarking shows that learned models are not automatically superior and the causal record is thin. The most defensible claim is that AI compresses decision latency and reallocates managerial attention from data assembly to exception handling, and that gains materialise only when the decision system is redesigned to use them.

References

[1] Lee, H.L., Padmanabhan, V. and Whang, S. (1997) The Bullwhip Effect in Supply Chains. Sloan Management Review, 38(3), 93-102.

[2] Min, H. (2010) Artificial Intelligence in Supply Chain Management: Theory and Applications. International Journal of Logistics Research and Applications, 13(1), 13-39. https://doi.org/10.1080/13675560902736537

[3] Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P. and Fischl, M. (2021) Artificial Intelligence in Supply Chain Management: A Systematic Literature Review. Journal of Business Research, 122, 502-517. https://doi.org/10.1016/j.jbusres.2020.09.009

[4] Baryannis, G., Validi, S., Dani, S. and Antoniou, G. (2019) Supply Chain Risk Management and Artificial Intelligence: State of the Art and Future Research Directions. International Journal of Production Research, 57(7), 2179-2202. https://doi.org/10.1080/00207543.2018.1530476

[5] Makridakis, S., Spiliotis, E. and Assimakopoulos, V. (2018) Statistical and Machine Learning Forecasting Methods: Concerns and Ways Forward. PLOS ONE, 13(3), e0194889. https://doi.org/10.1371/journal.pone.0194889

[6] Jackson, I., Ivanov, D., Dolgui, A. and Namdar, J. (2024) Generative Artificial Intelligence in Supply Chain and Operations Management: A Capability-Based Framework for Analysis and Implementation. International Journal of Production Research, 62(17), 6120-6145. https://doi.org/10.1080/00207543.2024.2309309

[7] Dubey, R., Gunasekaran, A., Childe, S.J., Bryde, D.J., Giannakis, M., Foropon, C., Roubaud, D. and Hazen, B.T. (2020) Big Data Analytics and Artificial Intelligence Pathway to Operational Performance under the Effects of Entrepreneurial Orientation and Environmental Dynamism: A Study of Manufacturing Organisations. International Journal of Production Economics, 226, 107599. https://doi.org/10.1016/j.ijpe.2019.107599

[8] Benzidia, S., Makaoui, N. and Bentahar, O. (2021) The Impact of Big Data Analytics and Artificial Intelligence on Green Supply Chain Process Integration and Hospital Environmental Performance. Technological Forecasting and Social Change, 165, 120557. https://doi.org/10.1016/j.techfore.2020.120557

[9] Sanders, N.R., Boone, T., Ganeshan, R. and Wood, J.D. (2019) Sustainable Supply Chains in the Age of AI and Digitization: Research Challenges and Opportunities. Journal of Business Logistics, 40(3), 229-240.https://doi.org/10.1111/jbl.12224