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Advances in Artificial Intelligence and Predictive Analytics for Supply Chain Risk Management and Demand Forecasting

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Abstract

The year 2025 marked a turning point in how artificial intelligence (AI) is applied to two of the most consequential problems in supply chain management: anticipating disruption and forecasting demand. Three developments converged. First, time-series foundation models matured from univariate research prototypes into covariate-aware, production-ready systems, most notably Amazon's Chronos-2 and Google's TimesFM 2.5, and became available through open-source releases and managed cloud services. Second, large language models (LLMs) and knowledge graphs began to turn unstructured news, regulatory notices and supplier documents into structured, network-aware risk signals. Third, agentic AI, meaning LLM-driven systems that plan, call tools and act, moved from vendor roadmaps into planning platforms, at the same time as a volatile tariff environment pushed firms toward AI-enabled scenario planning and digital twins.

Using an integrative literature review of 261 sources, comprising 243 applied studies screened from a consolidated peer reference list together with technical reports, preprints and industry surveys from Gartner, McKinsey, WTW and CIPS, the paper synthesises these advances. It finds that technical capability advanced faster than organisational readiness: model performance was rarely the binding constraint, whereas data quality, multi-tier visibility, governance and accountability for automated decisions frequently were. The paper proposes an integrated framework that links probabilistic demand forecasting, risk sensing and scenario simulation through a governed decision layer, together with six testable propositions. It then discusses theoretical, managerial and policy implications, and sets out future research directions covering evaluation under regime shifts, explainability, AI as a third-party risk domain and human oversight of autonomous agents.

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1. Introduction

Supply chains have operated under near-continuous stress since 2020. The pandemic, port congestion, armed conflict, extreme weather and, in 2025, a rapid sequence of tariff announcements and reversals exposed how thinly buffered many networks had become. Two analytical capabilities sit at the centre of any response. Demand forecasting determines how much to make, buy and position; supply chain risk management (SCRM) determines where the network is fragile and what to do before a disruption propagates. Both are fundamentally predictive problems, and both have been reshaped by recent advances in machine learning.

Before 2024, most organisations relied on per-series statistical models such as ARIMA and exponential smoothing, gradient-boosted trees trained on lagged features, or specialised deep learning architectures. Risk management depended on periodic supplier assessments, manual news monitoring and spreadsheets. Jahin *et al.* (2025) [138], in a systematic review of AI in supply chain risk assessment, documented a large and growing body of machine learning research but noted that the field had lacked a consolidated view of how these methods translate into risk mitigation practice.

Applied research across Africa, North America and Europe has also developed the risk and project-level foundations on which these newer methods build. Enterprise risk analytics and resilience frameworks provide the conceptual scaffolding for quantifying and prioritising supply chain exposure (Adeyelu, 2020; Falemi *et al*., 2024; Komi, 2025; Sakyi *et al*., 2024b) [13, 118, 143, 229]. Studies of EPC, infrastructure and project delivery show how supply risk concentrates in long-lead materials, schedules and contractor performance (Makut *et al*., 2021; Zhou *et al*., 2024) [150, 261].

Against this background, the paper addresses three research questions. RQ1: What were the principal advances in AI and predictive analytics for demand forecasting and supply chain risk management in 2025? RQ2: How do these advances fit together, and how do they relate to the wider applied literature on procurement, analytics, governance and enabling technologies? RQ3: What does the available evidence say about the conditions under which these advances create value, and what remains unresolved?

The paper makes three contributions. First, it synthesises 2025 developments in time-series foundation models, language-model-based risk sensing, digital twins and agentic AI alongside 243 applied studies drawn from a consolidated peer reference list. Second, it proposes a conceptual model that integrates forecasting, risk sensing, simulation and governed decision-making, together with testable propositions. Third, it derives theoretical, managerial and policy implications and sets out a structured agenda for future research.

The remainder of the paper is organised as follows. Section 2 describes the research method. Section 3 presents the results and discussion, including the literature synthesis, the conceptual model and propositions, and the theoretical, managerial and policy implications. Section 4 concludes and sets out directions for future research.

2. Research Method

2.1. Research Design

The study adopts an integrative literature review design, which is suited to emerging topics where evidence is spread across peer-reviewed research, preprints, industry surveys and practitioner reports, and where the aim is to synthesise knowledge into a new conceptual framework rather than to estimate a pooled effect. The review follows the general logic of systematic reviews, with explicit sources, inclusion criteria, screening and thematic coding, while accepting a broader evidence base than a narrow systematic review would allow.

2.2. Data Sources and Search Strategy

Evidence on 2025 developments was gathered from five categories of source published up to the end of 2025. Searches combined terms for the technology (artificial intelligence, machine learning, large language model, foundation model, agentic AI, digital twin, predictive analytics) with terms for the application (supply chain risk, disruption, supplier, procurement, demand forecasting, inventory). The source categories were:

- **Technical literature:** model technical reports and preprints (for example, the Chronos-2 report on arXiv), workshop papers on LLM-based risk analysis, and peer-reviewed journal articles.
- **Industry surveys:** Gartner predictions and market forecasts, the McKinsey 2025 Supply Chain Risk Pulse, the WTW Global Supply Chain Risk Report 2025 and the CIPS quarterly Pulse Survey.
- **Deployment reports:** model release notes and case studies published by model developers, such as Amazon's Chronos-2 release.
- **Practitioner analysis:** analyst commentary on AI adoption in supply chain and third-party risk management during 2025.
- **Consolidated peer reference list:** a deduplicated list of 1,056 applied studies organised into 68 subject areas, which was screened for relevance to the review questions (Section 2.4).

2.3. Inclusion and Exclusion Criteria

Sources were included if they (a) were published in or before 2025; (b) addressed AI, machine learning or predictive analytics applied to supply chain, procurement, operations, risk or an enabling capability such as data governance, cybersecurity, IoT or digital twins; and (c) reported a model, framework, empirical finding or survey result. Sources were excluded if they were dated after 2025, if their subject was unrelated to supply chain or operational decision-making (for example, clinical nursing practice, livestock nutrition or pedagogy), or if they duplicated another included source.

2.4. Screening and Selection

Screening proceeded in two passes. In the first pass, every entry in the consolidated list was scored for topical relevance using a weighted keyword scheme covering supply chain, procurement, forecasting, risk, analytics and AI terms. In the second pass, titles of candidate studies were reviewed manually to remove entries that scored highly on generic terms but were substantively unrelated, to remove duplicates and undated entries, and to remove studies published after 2025. This process yielded 243 studies classified as directly related (supply chain, procurement, forecasting and risk analytics) or semi-related (adjacent domains whose methods transfer, such as financial forecasting, fraud analytics and AI governance). They were combined with 18 sources documenting 2025 model releases, research and industry surveys, giving 261 references in total.

In addition to the sources above, the review integrates 243 applied studies drawn from a consolidated peer reference list, selected for direct or adjacent relevance to supply chain risk, procurement, forecasting, AI governance and enabling technologies. The review also draws on a broader body of applied AI and machine learning literature that informs the methods discussed here (Nwangwu *et al*., 2024b; Okonkwo *et al*., 2020) [168, 195].

2.5. Quality Appraisal

Vendor marketing claims were treated cautiously and are cited only where they describe a concrete product capability

rather than an outcome. Benchmark results reported by model developers are presented as such, since independent replication of time-series foundation model benchmarks is still limited.

2.6. Analysis and Synthesis

Included studies were coded inductively by their primary subject, producing twenty initial codes that were consolidated into seventeen thematic categories (Table 4). Themes were then mapped onto the review questions: technology advances (RQ1), relationships between capabilities and the wider literature (RQ2), and conditions for value creation (RQ3). The synthesis informed the conceptual model in Section 3.6. Table 1 summarises the review protocol.

Table 1: Summary of the review protocol

Element	Specification
Review type	Integrative literature review with systematic screening and thematic coding
Time frame	Publications up to and including 2025
Source types	Peer-reviewed articles, preprints and technical reports, industry surveys, developer release notes, and a consolidated peer reference list
Screening	1,056 consolidated-list entries screened by weighted keyword relevance, then by manual title review
Included studies	243 studies from the consolidated list plus 18 sources on 2025 developments (261 references)
Analysis	Inductive coding into 17 thematic categories; mapping to three research questions; conceptual model development

3. Results and Discussion

This section presents and discusses the results of the review. Sections 3.1 to 3.4 synthesise the literature in four strands that correspond to the main components of an AI-enabled supply chain decision system: the risk environment that created demand for new tools, advances in demand forecasting, advances in risk sensing and simulation, and the emergence of agentic AI as a connecting layer. Section 3.5 summarises the thematic structure of the reviewed literature. Section 3.6 develops the conceptual model and propositions, Section 3.7 discusses the findings in relation to the research questions, and Section 3.8 sets out the implications.

3.1. The 2025 Risk Environment

The demand for predictive tools in 2025 was driven by an unusually volatile operating environment. Several surveys captured its shape.

3.1.1 Tariffs and Geopolitical Uncertainty

According to McKinsey's Supply Chain Risk Pulse 2025 (McKinsey & Company, 2025) [155], tariffs became the defining global supply chain issue, with 39% of respondents reporting higher supplier and material costs. The Chartered Institute of Procurement & Supply found in its Q2 2025 Pulse Survey that 66% of respondents cited geopolitical risk or political uncertainty as a broad organisational concern, the highest level the survey had ever recorded, while concern about supplier instability rose from 28% to 36% in a single quarter.

Trade policy, customs regimes, cross-border payment rails and contractual force majeure provisions have been identified as recurrent sources of supply-side exposure (Adesuyi *et al*., 2025b; Akomolafe *et al*., 2022; Akomolafe *et al*., 2023; Akomolafe *et al*., 2024b; Annan, 2024; Eboh & Aliliele, 2025b; Jones & Ominyi, 2024a; Jones & Ominyi, 2025a; Uchechi *et al*., 2020) [10, 50, 51, 52, 70, 102, 139, 140, 248].

3.1.2 Cyber and Third-Party Risk

The risk mix also shifted toward digital exposure. WTW's 2025 Global Supply Chain Risk Survey reported that cybersecurity's share as a top supply chain risk rose from 5% in 2023 to 16% in 2025. As AI capabilities were embedded in supplier software and services, risk practitioners began to observe a related problem: organisations struggled to track where AI was being used internally and by their vendors, a problem often described as shadow AI.

3.1.3 A Paradox of Investment

Volatility increased the value of predictive analytics, yet it also consumed management attention. The McKinsey pulse found that the share of companies planning major investments in digital supply chain systems fell from 47% to 25% year on year, as tariff firefighting absorbed leadership time. The same survey identified demand forecasting, inventory optimisation and supply planning as the top three generative AI use cases in supply chains. In other words, the use cases were clear, but sustained investment was under pressure.

3.2. Advances in Demand Forecasting

3.2.1 From Univariate to Universal Foundation Models

Time-series foundation models (TSFMs) apply the large-model paradigm of natural language processing to sequential numeric data. A single model is pre-trained on a very large and diverse corpus of time series and can then forecast new series with no task-specific training (zero-shot) or with light fine-tuning. The first generation, released in 2024, including Chronos, TimesFM and Moirai, showed that this was feasible but was largely limited to univariate forecasting. That limitation mattered for supply chains, because demand is rarely a function of its own history alone. Promotions, prices, holidays, weather and the behaviour of related products all carry information.

The most significant 2025 advance closed this gap. Amazon released Chronos-2 in October 2025 as a model capable of univariate, multivariate and covariate-informed forecasting in a zero-shot manner (Ansari *et al*., 2025) [71]. Its architecture uses a group attention mechanism that lets related series, targets and covariates share information through in-context learning, and it accepts covariates that are past-only or known in the future, numeric or categorical. Amazon reported that its earlier Chronos and Chronos-Bolt models had already been downloaded more than 600 million times from Hugging Face, an indication of how quickly practitioners had adopted the approach.

On fev-bench, a benchmark that emphasises multivariate and covariate-informed tasks, the developers reported an average win rate of 90.7% and a skill score of 47.3% for Chronos-2, against 80.8% and 42.6% for the next best pretrained model, TiRex. The largest gains appeared on tasks with covariates, and Chronos-2 also ranked first among pretrained models on the GIFT-Eval benchmark at release. For supply chain users, the practical significance lies in two capabilities the

developers highlighted: incorporating known promotion schedules and holidays to capture real sales dynamics, and cross-learning between series, which helps in cold-start cases such as forecasting for a newly opened distribution centre using patterns from existing facilities.

Google's TimesFM 2.5, released in September 2025, followed a parallel path. It builds on the decoder-only architecture introduced by Das *et al*. (2024) [92], uses roughly 200 million parameters (Google Research, 2025) [126], and its release was accompanied by covariate support and integration into managed analytics services, allowing forecasts to be generated directly from SQL in BigQuery. Other notable 2025 models included Salesforce's Moirai-2, which uses multi-token prediction to generate several future values at once, and Time-MoE, a mixture-of-experts model pre-trained on approximately 300 billion time points. Leaderboard positions among these models shifted repeatedly through 2025, so rankings should be read as snapshots rather than settled results.

Table 2: Selected time-series foundation models relevant to demand forecasting (2025)

Model	Developer	Key 2025 capability	Relevance to demand forecasting
Chronos-2	Amazon	Group attention with in-context learning; multivariate and covariate-informed forecasting, zero-shot	Uses promotions, prices and holidays without retraining; cross-learning supports cold-start SKUs and new sites
TimesFM 2.5	Google Research	Decoder-only, ~200M parameters; covariate support; managed SQL access	Low-friction forecasting inside data warehouses; quick baselines across large item catalogues
Moirai-2	Salesforce	Multi-token prediction for efficient multi-step output	Faster inference for long horizons and large portfolios
Time-MoE	Academic	Mixture-of-experts pre-trained on ~300B time points	Scales capacity while limiting compute per forecast

Sources: Ansari et al. (2025); Amazon Science (2025); Das et al. (2024); Google Research (2025). Benchmark claims are as reported by model developers.

3.2.2 From Benchmark to Practice

The 2025 releases were designed for operational use rather than benchmark competition alone. The Chronos-2 technical report includes case studies in retail and energy showing that adding known covariates, such as promotion calendars and holidays for sales or grid load and renewable generation forecasts for energy prices, materially improved forecast quality relative to the same model run on history alone (Ansari *et al*., 2025) [71]. Amazon also made the model available for deployment through its managed machine learning service, and TimesFM can be called directly from SQL inside Google BigQuery (Amazon Science, 2025; Google Research, 2025) [62, 126].

The architectural lesson is that foundation models change where effort is spent. Traditional pipelines require a separate fitting and tuning step for each series or product family and frequent retraining as demand shifts. With a pre-trained model, routine forecast generation becomes an inference step, and adaptation, where needed, can be handled by lightweight fine-tuning on a slower cadence. This decoupling simplifies operations and reduces the engineering burden that historically limited how many forecasting models a planning team could maintain.

3.2.3 Probabilistic Forecasting as the Default

A less visible but consequential trend is that most leading 2025 models produce probabilistic outputs, typically quantile forecasts, rather than single point estimates. Benchmarks such as fev-bench evaluate models on scaled quantile loss rather than point error alone. For inventory and risk decisions this matters directly: safety stock, service-level targets and scenario planning all depend on the shape of the uncertainty, not just its centre. The convergence of forecasting and risk management, discussed in Section 3.6, rests on this shift.

3.2.4 Limits and Open Questions

Practitioners remain divided on whether a single pre-trained model can replace carefully tuned local models. Specialised gradient-boosted models on lagged features remain strong, interpretable and fast in many production settings, and a common recommendation is a hybrid: foundation models for initialisation, baselines and cold-start problems, with task-specific fine-tuning or ensembles for mature, high-volume series. A further concern is evaluation leakage. Because TSFMs are pre-trained on millions of public series, researchers have noted the possibility that benchmark or related series were seen during training, which can inflate reported accuracy.

3.2.5 Related Applied Forecasting Literature

Within supply chains specifically, earlier studies developed predictive and optimisation models for demand, inventory, materials planning and replenishment (Agbabiaka *et al*., 2019; Aifuwa *et al*., 2020; Akin-Oluyomi & Akhigbe, 2022; Akin-Oluyomi & Akhigbe, 2023b; Akin-Oluyomi & Akhigbe, 2023c; Anene, 2021; Ebisi, Alugwe *et al*., 2023; Ebisi, Sam-Bulya *et al*., 2023; Efobi *et al*., 2022b; Efobi *et al*., 2023; Ekwunife *et al*., 2024; Falemi *et al*., 2020; Falemi *et al*., 2023b; Filani *et al*., 2022) [14, 24, 27, 28, 29, 66, 96, 105, 106, 107, 116, 117, 119]. Further contributions in this stream extend these ideas to additional sectors and data environments (Gideon, 2025a; Ike *et al*., 2022; Mbonu *et al*., 2020a; Nnabueze *et al*., 2021; Obukadata, 2025; Ogundairo & Ayivi-Donkor, 2024a; Ogunwole *et al*., 2021; Okonkwo *et al*., 2018b; Okonkwo *et al*., 2024a; Okonkwo *et al*., 2024b; Okonkwo *et al*., 2024e; Okonkwo *et al*., 2024f; Okonkwo, Ahiaeke Patrick *et al*., 2023; Olagunju *et al*., 2024) [125, 131, 154, 162, 172, 180, 182, 189, 190, 193, 194, 198, 201, 209]. Additional studies reach consistent conclusions across different operational contexts (Ominyi *et al*., 2021; Oteri & Edivri, 2024; Rukh *et al*., 2024; Tonoyan *et al*., 2021a) [215, 222, 226, 240].

Forecasting research in energy and asset-intensive settings, including renewable yield, load and reservoir prediction, demonstrates the value of covariate-rich, probabilistic models (Akintola *et al*., 2025; Ezeugwa *et al*., 2023b; Ijiga *et al*., 2023b; Ilesanmi *et al*., 2024; Komi, 2021; Komi, 2023; Nnabueze *et al*., 2024; Nwangwu *et al*., 2020; Obriki & Arumosoye, 2018) [45, 114, 128, 133, 141, 142, 163, 167, 171]. Comparable forecasting and analytics architectures have been applied to financial, revenue and portfolio planning, offering transferable lessons on data integration and uncertainty quantification (Adesuyi *et al*., 2022; Agu *et al*., 2023b; Agu *et al*., 2025; Akomolafe & Agu, 2019b; Akomolafe & Agu, 2019c; Akomolafe *et al*., 2025; Basnet *et al*., 2024; Edivri &

Oteri, 2022; Filani *et al*., 2023; Isiekwu *et al*., 2025; Lawal & Oduleye, 2021a; Medon & Oduleye, 2024; Oduleye & Medon, 2023a; Okoruwa, Fadayomi *et al*., 2025) [11, 18, 19, 47, 48, 49, 87, 103, 120, 137, 147, 156, 175, 206]. Further contributions in this stream extend these ideas to additional sectors and data environments (Olagunju *et al*., 2022; Oluwo *et al*., 2025; Sakyi *et al*., 2023; Sanni *et al*., 2022; Tonoyan *et al*., 2021b; Tonoyan *et al*., 2022a; Tonoyan *et al*., 2025; Ukadike & Ibeh, 2023) [208, 211, 228, 231, 241, 242, 247, 251].

Customer, marketing and retail analytics provide demand-side signals that increasingly feed forecasting pipelines (Adeyelu, 2018; Basnet *et al*., 2021; Dada *et al*., 2021b; Nnabueze, Sakyi *et al*., 2023; Ogundairo & Ayivi-Donkor, 2023a; Oziri *et al*., 2020; Rukh *et al*., 2023b; Seyi-Lande *et al*., 2020; Wedraogo & Sanni, 2024) [12, 86, 91, 161, 179, 223, 225, 232, 256]. Predictive analytics has also been applied to early-warning problems in health, public services and safety, reinforcing a general shift from descriptive to anticipatory analytics (Adelanwa *et al*., 2024; Ahmed *et al*., 2020; Akinlolu *et al*., 2024; Aliliele *et al*., 2023c; Atakpa, Abolaji *et al*., 2024; Azeez & Badmus, 2024b; Ebisi *et al*., 2024; Ilodigwe & Adesemoye, 2024a; Ilodigwe & Adesemoye, 2025a; Michael & Ogunsola, 2023c; Oghenemaiga *et al*., 2024; Okwesa *et al*., 2024; Oparah *et al*., 2021; Oparah *et al*., 2022) [7, 22, 43, 58, 78, 82, 97, 134, 136, 159, 177, 207, 218, 219]. Further contributions in this stream extend these ideas to additional sectors and data environments (Oparah *et al*., 2024; Tonoyan *et al*., 2022c; Upreti & Oteri, 2023) [220, 243, 252].

3.3. Advances in Supply Chain Risk Sensing and Simulation

3.3.1 LLMs for Risk Identification and Classification

Most early warnings of supply chain disruption appear first in unstructured text: news reports, regulatory filings, port notices and supplier advisories. Historically, managers monitored these manually. In 2025, research matured on using LLMs to automate this step. Zhao *et al*. (2025) [259] described an LLM-based pipeline that collects real-time supplier news, interprets it with LLMs, classifies risks and assesses their likelihood and impact to generate alerts, and benchmarked several state-of-the-art LLMs on risk identification, including the effect of prompt engineering on accuracy.

Data-driven supplier evaluation, procurement risk management and supplier relationship frameworks form the organisational foundation on which AI risk sensing is built (Abdulrazaq *et al*., 2025; Ahiaeke Patrick *et al*., 2020; Ahiaeke Patrick *et al*., 2021; Akhigbe *et al*., 2023; Akin-Oluyomi *et al*., 2020; Akin-Oluyomi, Atima *et al*., 2023; Akinleye & Adeyoyin, 2021; Akinleye & Adeyoyin, 2022a; Akinleye & Adeyoyin, 2022b; Akinleye *et al*., 2023; Akokodaripon *et al*., 2023; Babatope *et al*., 2023; Bello *et al*., 2023; Ike *et al*., 2021) [1, 20, 21, 26, 30, 33, 37, 39, 40, 41, 46, 83, 88, 130]. Further contributions in this stream extend these ideas to additional sectors and data environments (Nwangwu *et al*., 2025; Obogo *et al*., 2019b; Okonkwo *et al*., 2018a; Okonkwo *et al*., 2019; Okonkwo *et al*., 2024c; Okonkwo *et al*., 2024d; Okonkwo *et al*., 2025; Okonkwo, Ogunwole *et al*., 2021; Okoruwa *et al*., 2024; Okoruwa, Babatope *et al*., 2025; Tonoyan *et al*., 2024a; Uzougbo *et al*., 2024; Wedraogo *et al*., 2025) [169, 170, 191, 192, 196, 197, 200, 203, 204, 205, 245, 254, 257].

Anomaly detection and machine learning techniques developed for fraud, audit and transaction monitoring transfer directly to detecting irregular supplier, shipment and payment patterns (Adebayo *et al*., 2023; Adelanwa *et al*., 2023b; Adesuyi *et al*., 2024; Adesuyi *et al*., 2025a; Aliliele *et al*., 2025a; Amadi *et al*., 2025b; Atakpa & Abetoh, 2022; Atakpa, 2021; Atakpa, Abetoh *et al*., 2024; Dosunmu & Ogundele, 2019; Eboh & Aliliele, 2023; Eboh & Aliliele, 2024; Elebe & Anunagba, 2025; Elebe *et al*., 2023) [4, 6, 8, 9, 59, 61, 75, 76, 77, 93, 100, 101, 108, 109]. Further contributions in this stream extend these ideas to additional sectors and data environments (Fadayomi *et al*., 2024; Fobellah, 2025a; Mbonu *et al*., 2022; Okojie, Filani *et al*., 2023; Okoli *et al*., 2022; Ominyi *et al*., 2024a) [115, 121, 153, 186, 188, 213].

3.3.2 Knowledge Graphs and Network-Aware Reasoning

A recurring finding is that text alone is insufficient: supply chain risk lives in relationships between firms, sites and materials. Two 2025 contributions illustrate the response. Zheng, Mizushina and Naono at Hitachi proposed an ontology-guided method in which an LLM iteratively extracts a supply chain risk knowledge graph from open data; their case study processed more than 7,000 news articles on Indian Ocean cyclone hazards to produce impact annotations for procurement officers.

Heus, Bookstaber and Sharma (2025) [127], presented at the ICAIF 2025 workshop, argued that standard retrieval-augmented generation oversimplifies relationships, and instead treated the supply chain network itself as a knowledge graph. A graph traverser guided by network centrality scores extracts the most economically salient risk paths, and an agentic layer combines this with numerical factor data and news streams. The authors also introduced descriptive templates that embed raw figures in natural language so that the LLM can reason about quantitative data, producing explainable risk narratives without costly fine-tuning or a dedicated graph database.

3.3.3 Multi-Agent Disruption Monitoring

By late 2025, research was moving from single-model pipelines toward multi-agent designs in which separate components detect signals, map them onto supplier networks and assess exposure. The approach of Heus *et al*. (2025) [127] already illustrates this pattern, with a routing agent selecting among factor data, news and the supply chain knowledge graph. The motivation is a well-known gap: graph-based propagation models can quantify how shocks cascade through networks but require structured input, whereas disruption signals emerge first in unstructured text. Agentic systems are proposed as the bridge between the two, with the aim of shortening the time between a distant event and an informed response.

3.3.4 Third-Party Risk at Scale

In third-party risk management, 2025 saw AI applied to continuous monitoring rather than periodic assessment. Vendors and practitioners describe AI scanning large supplier populations for signals no human team could track, including ownership changes, sanctions exposure, geographic risk, subcontractor relationships and adverse events, and AI agents extracting information from supplier-submitted documents to pre-populate assessments and flag items for follow-up. The common thread is triage: AI narrows attention to the suppliers and issues that warrant human review.

Pharmaceutical and cold chain studies highlight risk sensing in settings where product integrity, regulatory compliance and access to medicines are at stake (Akin-Oluyomi *et al*.,

2023b; Akin-Oluyomi *et al*., 2024; Akinleye, 2024; Aneke & Adesemoye, 2020; Aneke & Adesemoye, 2021; Aneke & Adesemoye, 2025; Asiedu & Asiedu, 2023b; Asiedu, 2025; Awulu *et al*., 2022b; Eze *et al*., 2023; Eze *et al*., 2024b; Ike *et al*., 2024b; Obukadata *et al*., 2021a; Opara *et al*., 2025) [28, 32, 38, 63, 64, 65, 73, 74, 80, 111, 112, 129, 173, 216].

3.3.5 Digital Twins and Tariff Scenario Planning

Tariff volatility in 2025 accelerated adoption of digital twins: dynamic, data-driven replicas of the end-to-end network used to simulate disruptions and evaluate responses. Several vendors released tariff-specific tools. Altana introduced a Tariff Scenario Planner in January 2025 built on its digital model of the global supply chain (Lowdown Blog, 2025) [149], and Coupa embedded AI-driven tariff and scenario planning into its supply chain suite. Reported outcomes include a European electronics firm that, by simulating tariff scenarios, found that 30% of its supplier network became cost-inefficient above a particular tariff threshold (Rutgers Business School, 2025) [227], and Vinmar, which reduced expedites by 20% using a real-time process-based digital twin (VentureBeat, 2025) [255].

An important conceptual shift accompanied these tools. Practitioners increasingly argued that predicting specific tariff outcomes was not feasible and that the goal should instead be preparing robust responses to a range of possibilities. In this framing, AI's role in risk management moves from point prediction to rapid scenario generation and evaluation.

Digital twin, IoT and predictive maintenance research supplies much of the sensing and simulation infrastructure on which network-level twins depend (Adaramola *et al*., 2018; Akinlade *et al*., 2024; Anene & Clement, 2022; Ike *et al*., 2025; Komi & Adamolekun, 2021; Komi & Adeniji, 2023; Kumuyi *et al*., 2024a; Mayo *et al*., 2021; Mensah *et al*., 2019; Nwangwu *et al*., 2023; Ojukwu *et al*., 2023; Okonkwo, Agbabiaka *et al*., 2021; Okonkwo, Mayo *et al*., 2023; Olodo *et al*., 2025) [2, 36, 67, 132, 144, 145, 146, 151, 157, 166, 183, 196, 198, 210]. Further contributions in this stream extend these ideas to additional sectors and data environments (Shittu & Shittu, 2024; Shittu *et al*., 2023; Shittu *et al*., 2024; Shittu *et al*., 2025; Sunday *et al*., 2020; Tonoyan *et al*., 2023; Uduokhai *et al*., 2025b) [234, 235, 238, 239, 244, 250].

Table 3: Mapping 2025 AI techniques to supply chain risk management tasks

Risk management task	2025 technique	What it adds
Signal detection	LLM-based extraction and classification from news, filings and advisories	Converts unstructured text into structured, timely alerts
Exposure mapping	LLM-extracted knowledge graphs; network-centrality retrieval	Links an external event to the specific suppliers, tiers and parts affected
Impact assessment	Graph-based propagation models; agentic orchestration	Estimates how a shock cascades and which paths matter economically
Response planning	Digital twins with AI-driven scenario simulation	Compares sourcing, inventory and routing options before committing
Supplier oversight	Continuous AI monitoring of third parties	Scales screening for sanctions, ownership and adverse events

Sources: Zhao et al. (2025); Zheng et al. (2025); Heus et al. (2025).

3.4. Agentic AI as the Connecting Layer

If 2024 was dominated by generative AI assistants, 2025 was the year agentic AI entered supply chain strategy. In May 2025 Gartner placed agentic AI at the top of its supply chain technology trends and predicted that half of supply chain management solutions would include agentic capabilities by 2030. Gartner also anticipated that by 2028, 15% of day-to-day supply chain decisions would be made autonomously by AI agents, while cautioning that full automation would not arrive in 2025 (Gartner, 2025a; Consumer Goods Technology, 2025) [90, 123].

Gartner positioned these predictions as the start of a staged transition, in which agents first act as task-specific assistants to human planners before taking on more autonomous, multi-step workflows (Gartner, 2025a) [123]. On this view, 2025 was the starting point of the adoption curve rather than its peak.

Conceptually, agents are the mechanism that connects the forecasting and risk capabilities described above. An agent can read a disruption alert, query the knowledge graph for exposed suppliers, request a revised probabilistic forecast that includes the disruption as a covariate, run scenarios in a digital twin and draft a recommended action for a planner. Each component existed before 2025; what changed was the ability to orchestrate them through language and tool use.

Related work on multi-agent architectures, autonomous robotics and warehouse automation shows how autonomous agents are already coordinating physical and digital operations (Akanbi *et al*., 2025; Badmus *et al*., 2025; Ebisi *et al*., 2022; Nwakamma *et al*., 2024b; Odejobi *et al*., 2025; Ogundairo & Ayivi-Donkor, 2024b; Ogundairo, 2025; Ominyi *et al*., 2025a) [25, 84, 99, 165, 174, 178, 181, 214]. Decision support systems and AI-driven business intelligence frameworks offer design patterns for the planner-facing layer of agentic systems (Agboada *et al*., 2018; Ezeako *et al*., 2024; Michael & Ogunsola, 2025c; Sanni & Attah, 2023b; Shah *et al*., 2025; Tonoyan *et al*., 2024b) [16, 113, 160, 230, 233, 246].

Gartner itself paired this optimism with a warning, predicting in June 2025 that over 40% of agentic AI projects would be cancelled by the end of 2027 (Gartner, 2025b) [124] because of escalating costs, unclear business value or inadequate risk controls. Section 3.7 discusses why.

3.5. Thematic Structure of the Reviewed Literature

Table 4 summarises how the 243 studies from the consolidated reference list are distributed across the seventeen thematic categories identified during coding. The distribution shows that the applied literature is most dense in supply chain planning analytics, procurement and supplier management, financial forecasting, digital twins and IoT, and anomaly detection, and comparatively thin on AI governance, decision support design and workforce capability.

Counts reflect each study's primary thematic code; studies were assigned to one category only.

Three cross-cutting patterns emerge. First, most applied studies propose conceptual frameworks or single-setting models rather than comparative evaluations, which limits

generalisation. Second, methods developed in adjacent domains, particularly fraud detection, financial forecasting and predictive maintenance, transfer readily to supply chain problems but are rarely tested there directly. Third, governance, security and workforce capability, which the 2025 evidence identifies as the main barriers to value, receive far less attention than model design.

Table 4: Thematic distribution of the reviewed studies (n = 243)

Thematic category	Studies	Primary link to this review
Supply chain demand, inventory and planning analytics	32	Demand forecasting (3.2)
Procurement and supplier management	27	Risk sensing (3.3)
Financial, revenue and portfolio forecasting	22	Demand forecasting (3.2)
Digital twins, IoT and predictive maintenance	21	Simulation (3.3)
Fraud, audit and anomaly detection	20	Risk sensing (3.3)
Sustainability, ESG and circular supply chains	20	Future research (4.2)
Early-warning predictive analytics (health, safety, public services)	17	Demand forecasting (3.2)
Pharmaceutical and cold chain supply	14	Risk sensing (3.3)
Trade, customs and cross-border transactions	9	Risk environment (3.1)
Energy and renewable forecasting	9	Demand forecasting (3.2)
Customer, marketing and retail analytics	9	Demand forecasting (3.2)
Agents, robotics and warehouse automation	8	Agentic AI (3.4)
Cybersecurity and operational technology security	8	Discussion (3.7)
AI governance and regulatory compliance	6	Discussion (3.7)
Decision support and business intelligence	6	Agentic AI (3.4)
Enterprise risk and project supply chains	6	Introduction (1)
Workforce, lean operations, data foundations and general AI	9	Discussion (3.7)

3.6. Conceptual Model

3.6.1 Model Structure

The literature synthesis points toward an architecture in which demand forecasting and risk management are no longer separate functions with separate tools. Figure 1 presents an integrated conceptual model that organises the reviewed capabilities into four layers, connected by two-way links between forecasting and risk sensing, a feedback loop from decisions back to data, and a set of organisational moderators drawn from the discussion of failure modes.

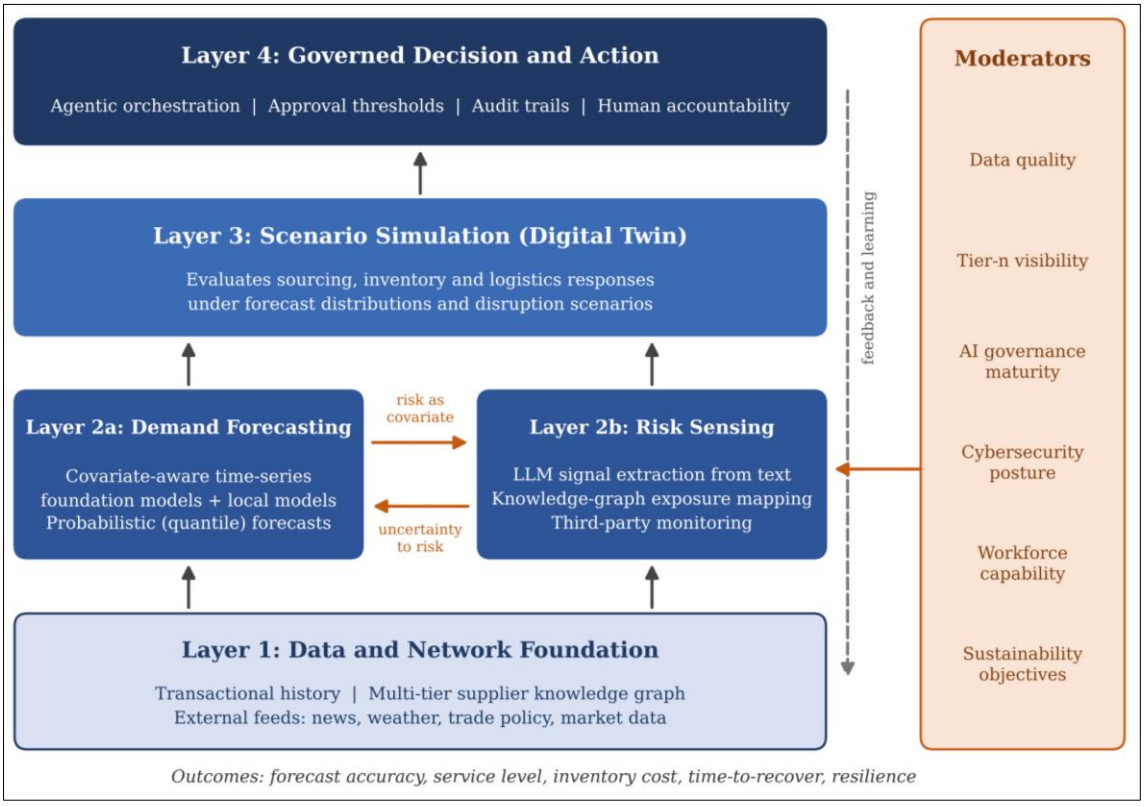


Fig 1: Integrated conceptual model of AI-enabled demand forecasting and supply chain risk management

- **Layer 1, Data and network foundation:** clean transactional history, a multi-tier supplier network represented as a knowledge graph, and curated external feeds covering news, weather, trade policy and market data.
- **Layer 2, Sensing and prediction:** covariate-aware probabilistic demand forecasts from foundation models (with local models where they perform better), alongside LLM-based risk signal extraction mapped onto the network.
- **Layer 3, Simulation:** a digital twin that takes forecast distributions and risk scenarios as inputs and evaluates sourcing, inventory and logistics responses under each.
- **Layer 4, Governed decision and action:** agents that orchestrate layers 2 and 3 and propose actions, with explicit approval thresholds, audit trails and named human accountability for decisions above defined risk or value limits.

The critical linkage is that a detected risk becomes a covariate or scenario for the forecast, and the forecast's uncertainty becomes an input to risk response. A port closure, for example, changes expected supply; a competitor's disruption may change expected demand; both flow into the same simulation. The governance layer is not an afterthought. The 2025 evidence suggests it is the main determinant of whether the upstream layers create value.

The model also specifies moderators that condition the strength of each relationship: data quality, visibility beyond tier-one suppliers, AI governance maturity, cybersecurity posture, workforce capability and sustainability objectives. Outcomes are assessed at the level of decisions rather than models: forecast accuracy, service level, inventory cost, time-to-recover and overall resilience.

3.6.2 Propositions

The model yields six propositions that can be tested in future empirical work (Table 5).

Table 5: Propositions derived from the conceptual model

No.	Proposition
P1	Covariate-aware probabilistic forecasts from foundation models improve forecast accuracy and service level relative to univariate baselines, with the largest gains for new products, new sites and periods with known external drivers.
P2	Feeding structured risk signals into forecasting as covariates or scenarios improves forecast performance during disruptions more than during stable periods.
P3	Network-aware risk sensing that combines language models with multi-tier supplier knowledge graphs shortens the time between a distant event and an informed response, compared with text-only monitoring.
P4	Scenario simulation in a digital twin improves the quality of disruption responses, as measured by cost and time-to-recover, when it is driven by forecast distributions rather than point forecasts.
P5	The positive effects in P1 to P4 are moderated by data quality and tier-n visibility: weak foundations reduce or eliminate the benefits of more capable models.
P6	Agentic orchestration creates value only where explicit approval thresholds, audit trails and named human accountability are in place; without them, agentic projects are more likely to be abandoned.

3.7. Discussion

This section interprets the synthesis in relation to the research questions. On RQ1, the evidence shows clear technical progress in 2025: universal, covariate-aware forecasting models; language-model pipelines that convert unstructured text into structured, network-aware risk signals; tariff-oriented digital twins; and the first agentic orchestration of these components. On RQ2, the conceptual model shows that these capabilities are complementary rather than separate, and the applied literature supplies transferable methods from adjacent domains. RQ3, concerning the conditions for value, is the subject of the remainder of Section 3.7.

3.7.1 The Value Gap

The 2025 record is mixed. MIT's 2025 GenAI Divide report found that 95% of enterprise generative AI pilots produced no measurable financial impact, despite significant investment (Fortune, 2025) [122]. The supply chain evidence reviewed here points to a consistent conclusion: AI did move from experimentation into execution where problems were well defined, particularly document review, data classification, anomaly detection and continuous monitoring, but in supply chains and risk management the limiting factor was rarely model performance.

3.7.2 Recurring Failure Modes

- **Data foundations.** Fragile, fragmented master data and inconsistent supplier records were manageable in manual workflows but became structural blockers once automation was introduced.
- **Visibility beyond tier one.** McKinsey's 2025 pulse found that 95% of firms have visibility into tier-one supplier risks but only 42% extend it to tier two or beyond (McKinsey & Company, 2025) [155]. Network-aware risk models are only as useful as the network data they are given.
- **Governance lag.** AI adoption outpaced oversight and accountability. Many organisations had not defined who approves AI-driven actions or who is accountable when automated recommendations introduce risk.
- **AI as an unmanaged risk.** For some firms AI was still not formally treated as a risk domain, even as it influenced sourcing, logistics and compliance decisions, including through capabilities delivered by vendors.
- **Attention scarcity.** Crisis management displaced longer-term digital investment, as reflected in the fall in firms planning major digital supply chain investments.

Research on responsible AI governance, algorithmic accountability and compliance monitoring addresses precisely the oversight gaps observed in 2025 (Alieme *et al*., 2025b; Atima *et al*., 2022; Mbonu *et al*., 2018; Ominyi & Anichukwueze, 2024; Osinem *et al*., 2025b; Uchechi *et al*., 2022) [57, 79, 152, 212, 221, 249]. Cybersecurity research on operational technology, cloud environments and attacks on AI workflows underlines why AI systems must themselves

be treated as a risk domain (Adebayo *et al*., 2022; Adegbite *et al*., 2024b; Ahmed *et al*., 2021; Amadi *et al*., 2025a; Dosunmu & Ogundele, 2024b; Ogbole *et al*., 2025; Shittu & Nabil, 2023; Upreti & Oteri, 2025) [3, 5, 23, 60, 94, 176, 234, 253].
Data integration, data quality and digital transformation studies confirm that weak data foundations, rather than model capability, are a common barrier to realising analytics value (Akinola *et al*., 2024; Michael & Ogunsola, 2021c; Oziri *et al*., 2025) [44, 158, 224]. Workforce, lean operations and organisational performance research indicates that human capability and process discipline determine whether analytics investments are absorbed (Alieme *et al*., 2024; Alieme *et al*., 2025a; Anene *et al*., 2025; Eyetsemitan *et al*., 2024b) [55, 56, 69, 110].

Table 6: Selected 2025 indicators on supply chain risk and AI adoption

Indicator	Value	Source
Respondents citing geopolitical or political uncertainty as a top organisational risk (Q2 2025)	66% (record high)	CIPS
Cybersecurity as a top supply chain risk, 2023 vs 2025	5% to 16%	WTW
Firms reporting higher supplier and material costs due to tariffs	39%	McKinsey
Firms planning major digital supply chain investment, year on year	47% to 25%	McKinsey
Agentic AI projects predicted to be cancelled by end of 2027	>40%	Gartner

Survey figures are as reported by the cited organisations.

3.7.3 Reconciling Capability and Readiness

Taken together, the findings suggest a widening gap between what AI can do and what organisations are prepared to absorb. Model capability improved quickly during 2025, while the enabling conditions identified as moderators in the conceptual model changed slowly. This explains why benchmark gains did not translate consistently into financial results and why Gartner expected a large share of agentic projects to be abandoned. It also suggests that the next phase of progress will depend less on new model architectures than on data foundations, network visibility, governance and the skills of the people who use these systems.

3.8. Implications

3.8.1 Theoretical Implications

The study contributes to supply chain risk management theory by treating forecasting and risk management as coupled components of a single decision system rather than as separate functions. The conceptual model extends resilience perspectives, which emphasise time-to-survive and time-to-recover, by specifying how predictive and generative AI capabilities affect those outcomes and which organisational conditions moderate the effect. It also supports a socio-technical view of AI in operations: the 2025 evidence suggests that the performance of AI-enabled supply chains is jointly determined by model capability and by governance, data and human factors, and theories that focus on either alone are incomplete.

3.8.2 Managerial Implications

- **Invest in foundations first.** Master data quality and multi-tier supplier mapping should precede, or at least accompany, investment in advanced models, since they determine whether those models add value.
- **Use foundation models pragmatically.** Time-series foundation models are well suited to cold-start items, new sites and rapid baselines; mature, high-volume series may still be better served by tuned local models or ensembles.
- **Connect risk and forecasting teams.** Risk signals should flow into forecasts as covariates or scenarios, and forecast uncertainty should inform risk responses.
- **Plan for scenarios, not point predictions.** Under trade and geopolitical uncertainty, the value of AI lies in evaluating many possible futures quickly rather than predicting a single one.
- **Govern agents before scaling them.** Define approval thresholds, audit trails and accountable owners for agent-initiated actions, and treat suppliers' AI systems as part of third-party risk.

3.8.3 Policy Implications

For policymakers and regulators, the findings highlight three priorities. First, greater transparency and data sharing on trade measures and supply chain structure would improve the inputs on which predictive models depend. Second, AI governance frameworks should address automated decisions in procurement, logistics and compliance, including those made by vendors on behalf of buyers. Third, programmes that support small and medium enterprises and firms in emerging markets to build data infrastructure and analytics skills would help ensure that the benefits of these technologies are not confined to large organisations.

4. Conclusion

The technical advances of 2025 were substantial. Time-series foundation models gained the ability to use covariates and related series without retraining, and their developers documented gains on retail and energy forecasting tasks. LLMs combined with knowledge graphs began to turn unstructured signals into network-aware risk intelligence. Digital twins became practical tools for navigating tariff uncertainty, and agentic AI emerged as the orchestration layer that could link these capabilities.
Yet the year's central lesson is organisational rather than technical. Where value was lost, the cause was usually data quality, limited visibility beyond direct suppliers, unclear accountability or governance that lagged adoption, not model accuracy. Organisations that treat forecasting, risk sensing and simulation as one governed system, invest in network data and define clear human ownership of automated decisions are best positioned to convert 2025's advances into durable resilience.

4.2. Future Research

Building on the gaps identified in the synthesis, the following directions merit priority:

- **Evaluation under regime shifts.** Benchmarks largely measure accuracy under stable conditions. Supply chain value is concentrated in periods of disruption, such as tariff shocks, when historical patterns break. Purpose-built stress-test benchmarks and leakage-controlled evaluation of foundation models are needed.

- **Decision-centric metrics.** Forecast accuracy and alert precision are proxies. Research should connect model outputs to inventory cost, service level, time-to-recover and margin outcomes.
- **Explainability for planners.** Natural-language risk narratives grounded in network paths are promising, but their faithfulness to the underlying data requires systematic testing.
- **AI as a third-party risk domain.** Methods are needed to assess how suppliers' own AI systems, data dependencies and automated decisions create exposure for their customers.
- **Human oversight of agents.** Which decisions should be autonomous, which require approval, and how should accountability be assigned when agents act across organisational boundaries?
- **Testing the propositions.** Empirical studies, including field experiments, panel surveys and simulation, should test propositions P1 to P6, particularly the moderating role of data quality and governance.
- **Inclusive deployment.** Most evidence comes from large firms. Small and medium enterprises, and supply chains in emerging markets with sparser data, remain under-studied, although the zero-shot and cold-start properties of foundation models may particularly benefit them.

Sustainability, ESG and circular-economy studies point to the need to embed environmental and social objectives in AI-enabled supply chain decisions. Further contributions in this stream extend these ideas to additional sectors and data environments.

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