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BEYOND PREDICTIVE ACCURACY: ARTIFICIAL INTELLIGENCE IN SUPPLY CHAIN RISK MANAGEMENT: A SYSTEMATIC INTEGRATIVE REVIEW AND RESILIENCE FRAMEWORK

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Abstract

AI is becoming more of an integral part of supply chain planning, monitoring, forecasting, supplier management, logistics, and disruption response. However, as the number of technically complex applications has grown so quickly, there is an important conceptual challenge: increased prediction doesn't necessarily mean increased supply chain resilience. This research systematically synthesizes empirical studies, systematic review, analytical frameworks, and application-oriented research on artificial intelligence (AI) for supply chain risk management (SCRM) published between 2020 and 2026 in a bounded corpus of 23 publications. The review considers the role of Machine Learning, Deep Learning, Predictive Analytics, Explainable Artificial Intelligence, Internet of Things enabled systems, and Reinforcement Learning in the processes of Risk Identification, Assessment, Mitigation and Monitoring. There are four key findings in the synthesis. AI has driven SCRM to be more anticipatory and data driven, especially regarding demand forecasting, evaluating supplier risk, forecasting, logistics control and operational optimization. Second, empirical evidence suggests that although AI can help to predict, it can also mitigate supply chain risks on the firm level in ways other than prediction, like better resource allocation. Thirdly, organizational value is dependent upon data quality, technological maturity, explainability, managerial control and ability to translate analysis findings into action. Fourth, the literature is still divided between technically oriented publications which focus on the performance of models and management-oriented publications whose focus is on resilience, implementation and governance. On the basis of these findings, the paper proposes an integrative AI-to-resilience translation framework that incorporates data infrastructure, AI analytical capability, strengthening of SCRM processes, and the strengthening of visibility, agility, adaptability, and resilience by SCRM processes. Explainability, organizational readiness, and governance are key enabling factors. The review challenges the main research question from the perspective of when, how, and under what organizational conditions predictive intelligence becomes resilience – instead of the question of whether it does or does not.

Keywords: Artificial Intelligence, Supply Chain Risk Management, Supply Chain Resilience, Machine Learning; Predictive Analytics; Explainable AI, Digital Twins; Human-AI Collaboration, Systematic Integrative Review

1. Introduction

Global supply chains are increasingly interacting networks of suppliers, manufacturing plants, logistics suppliers, information systems and customers. This interconnection is efficient but also exposes. A supply chain disruption can spread quickly across multiple layers of a supply chain, from one supplier, transport corridor, production site, information platform, or market. Structural challenge of traditional supply chain risk management: A decision is often required prior to the complete identification, understanding or impact of a disruption. Artificial intelligence (AI) is now being increasingly portrayed as a solution to this problem in recent years. Machine learning, deep learning, predictive analytics, natural language processing, intelligent optimization, and other types of computational methods enable organisations to analyse vast quantities of data that goes beyond traditional data formats, uncover patterns that might not be recognisable by humans, and make informed decisions as the world evolves (Daios et al., 2025; Nawrin et al., 2025; Teixeira et al., 2025).

Recent research has extended beyond demand forecasting (Bansal, 2025; Ngunjiri, 2021) and supplier relationship and risk management (Adesola et al., 2025) to the development of early-warning systems (Huang, 2025), predictive disruption management (Hasan, 2025), proactive mitigation (Larbi et al., 2025), multi-level risk-control strategies (Yang et al., 2025), customs and security risk management (Vijayakumar, 2025), digital twins and control towers (Tathed, 2025), and a wide range of applications of AI in other supply chain activities (Daios et al., 2025; Oliveira et al., 2025). This growth has generated a lot of optimism. These are often the terms with which AI is linked: faster detection and more accurate forecasts, improved visibility, more responsive inventory decisions, automated risk assessment, and adaptive optimization. But, there is a more nuanced picture in the steadily expanding body of research. The capability of technically capable models relies on the quality of the data used, sophisticated predictions can be ignored by managers, black-box systems can undermine trust, algorithms trained in one environment may transfer poorly to another, and sophisticated applications may be experimental rather than operational (John et al., 2025; Jahin et al., 2025; Vankayalapati & Banerjee, 2026).

So, the big question is now no longer just if but how AI can aid in SCRM. It is now well established that it can. The more important question is how technical AI capability transforms to becoming an organizational capability that results in measurable resilience. This is crucial as there are differences between predictive performance and organizational resilience. An algorithm can be correct in predicting when a supplier is likely to fail and yet be of no value to the organization if decision makers fail to trust the prediction, if procurement options are unavailable, if it is too late to provide managers with information about the supplier, or if contractual arrangements prevent quick substitution of suppliers. Likewise, an accurate demand forecast does not necessarily mean that the shortage or inventory cost will decrease. The benefit of the operation depends on the extent to which the prediction is incorporated into the planning process, resource allocation and also into the process of execution. Empirical studies recently support this separation. Based on the firm-level data of 1367 A-share listed companies in China from 2008 to 2023, Tian et al. (2025) reveal that AI adoption is negatively linked to supply chain risk, and that better resource-allocation efficiency is a possible explanation. This helps to move the discussion away from AI as a forecasting tool to AI as an organizational tool that will impact how companies allocate inventory, information, and other resources.

Meanwhile, explainability, data bias and human-AI collaboration studies reveal that technological sophistication is not enough to ensure reliable deployment (Ferrara & Isgrò, 2025; John et al., 2025). So, there's two somewhat disjointed conversations in the literature. A technical stream focuses on algorithms, prediction, optimization, deep learning, and reinforcement learning, as well as data processing. An organizational stream is about being resilient, ready, trusted, governed, collaborative, and implemented. Some existing reviews have contributed to the mapping of AI applications (Daios et al., 2025; Teixeira et al., 2025), AI and machine-learning approaches to SCRM (Jahin et al., 2025), technological maturity and effects (Oliveira et al., 2025), and deep-learning applications in SCRM throughout the LIF (Ghouati et al., 2025; Vankayalapati & Banerjee, 2026). An explanation of the translation mechanism linking technical intelligence with organizational resilience is less developed.

This review seeks to fill that gap. The study does not focus exclusively on the algorithms employed, but rather on the contributions that AI can make to the SCRM process and why the same technology could yield varying results in different organizational settings. It builds an integrative framework in which AI capability generates value by means of SCRM process capabilities and wider dynamic supply chain capabilities, under human, technological and governance conditions.

The study addresses five research questions:

RQ1. How is AI being used in various activities and risk situations within the supply chain?
RQ2. How can AI contribute to the identification, assessment, mitigation, monitoring, and building resilience to risk?
RQ3. What are the technological, organizational, human and governance conditions that facilitate or hinder AI powered SCRM?
RQ4. Which theoretical and methodological gaps or gaps in the evidence base are still present?
RQ5. What is the best way to connect the dots between the evidence and the framework for translating AI capability to supply chain resilience?

The paper has three contributions: First, it distinguishes between technical performance and effects on the organisation, which makes it less likely to use the prediction accuracy as an indicator of being resilient. Second, it jumps between the AI technologies and the organizational practices that create meaningful SCRM practices from the AI outputs. Thirdly, it builds an AI to resilience translation framework, incorporating data quality, human judgment, organizational readiness, and responsible governance within the causal narrative for AI-enabled resilience—rather than outside of it.

2. Conceptual Background

2.1 Supply Chain Risk Management

SCRM refers to processes of identifying, assessing, controlling, monitoring and mitigating events or circumstances that can hinder the continuity or performance of supply chains. Risk can come from within the focal organization, from suppliers or logistics partners or from the broader technological, economic, environmental and geopolitical arena.

SCRM is particularly challenging in the modern era, where risks are interdependent. A suppliers issue may cause manufacturing delays, which may affect logistics schedules, logistics disruption may cause inventory shortfalls, shortfalls may cause behavioural changes at customers, emergency responses may lead to secondary cost or capacity issues elsewhere in the network.

Historical data, expert judgment and risk registers, scoring models, scenario analysis, contingency plans, failure mode assessment, and probabilistic approaches have all been traditionally used. These are helpful at times when data is sparse or managerial knowledge is essential. They tend to display their shortcomings more clearly under conditions characterized by dynamic change and/or an overload of information that is too large and too varied for the human mind to process and handle "manually" (Bidin et al., 2024; Vankayalapati & Banerjee, 2026). AI transforms the capability of SCRM to process information. Rather than relying on pre-established thresholds or periodic evaluations, AI-powered systems can continually evaluate incoming observations, identify aberrant patterns, and assess potential interventions, as well as forecast outcomes and compare various decisions.

2.2 From Reactive Risk Management to Anticipatory SCRM

A "shift from reactive to anticipative risk management" is one of the most apparent emerges in the reviewed literature. Bidin et al. (2024) define post-pandemic SCRM as being an adaptive response, in contrast to pre-pandemic contingency planning. The integrated hardware-software architectures, where the sensors, RFID, GPS and AI-based analytical platforms are always collecting and analyzing operational data, are also conceptualized by Balasubramanian and Gurushankar (2020).

The difference is a core one. Reactive SCRM asks: What has occurred and what will be done about it? In the future, AI will increasingly ask, but with SCRM: What is so happening, what could, and what should they do before the disruptions become serious? Huang (2025) specifically looks at Early Warning with the help of AI; Larbi et al. (2025) at Proactive Disruption Mitigation; Yang et al. (2025) at Multi-level Risk Control using AI and Tathed (2025) at Resilient Supply Chain Management via integrated control towers and digital-twin simulations. Add them up to see how they show a shift from risk analysis in the past to sensing, forecasting, simulation and adapting all the time.

2.3 Supply Chain Resilience as an Outcome

Resilience isn't just about survival. A resilient supply chain needs to be able to sense emerging threats, withstand disturbances, adapt to them, sustain operations, and recover and reconfigure if needed.

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AI can potentially contribute to several capabilities that underpin resilience:

- **visibility**, by integrating and interpreting information across the network;
- **anticipation**, by identifying patterns associated with future disruption;
- **agility**, by shortening the time between detection and response;
- **flexibility**, by evaluating alternative sourcing, routing, or inventory decisions;
- **adaptability**, by learning from changing conditions;
- **coordination**, by distributing information and recommendations across supply-chain actors.

The thing to remember is that resilience is not the same as AI! It provides information and analysis power. Capacity needs to be translated into action through organizational processes.

3. Artificial Intelligence Capabilities Relevant to SCRM

3.1 Machine Learning and Predictive Analytics

The most common AI family that is represented in the reviewed literature is machine learning. Algorithms are trained on historical or real-time data to identify patterns, which are then applied to classify events, predict values or forecast future events.

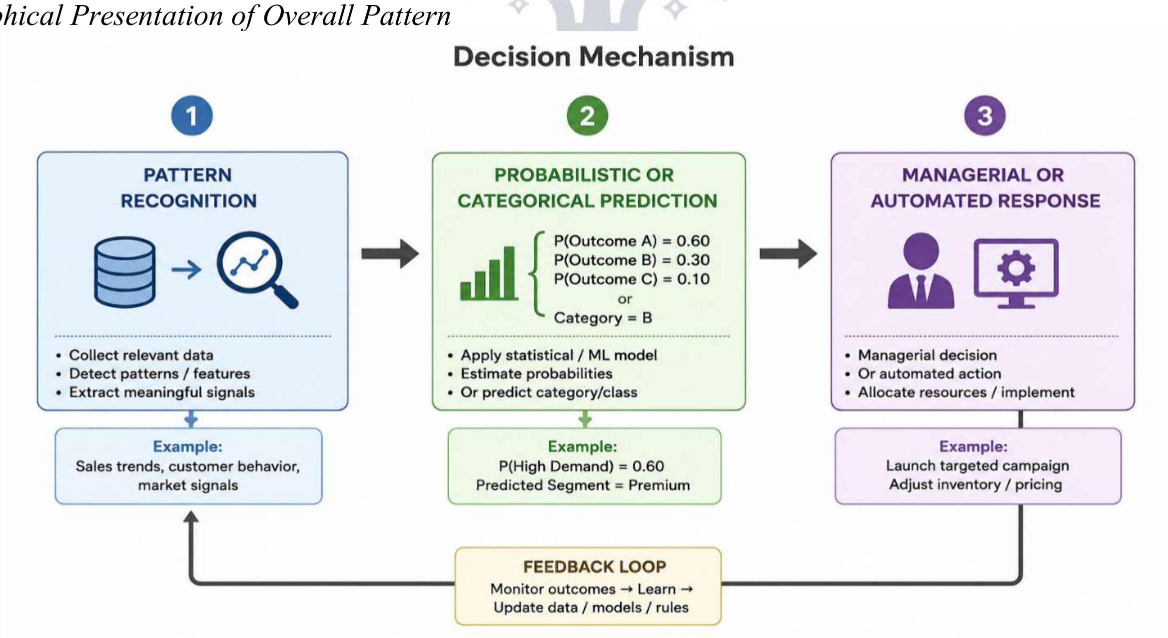
An early, but well-established application is demanding forecasting. Bansal (2025) investigates the role of AI-based demand forecasting in enhancing supply chain resilience, and Ngunjiri (2021) proposes a hybrid predictive analytics model for manufacturing demand forecasting. Forecasting is important to the risk management field because it presents a risk in itself if unanticipated, and because it can impact inventory, procurement, capacity planning and service.

Predictive analytics isn't just for demand. Huang (2025) is interested in early-warning risk detection, while Hasan (2025) is concerned with information-system-based predictive analytics, related to supply chain disruption. Adesola et al. (2025) explore the application of AI and machine-learning in supplier relationship management and risk mitigation.

The overall pattern is the same for all three situations:

Figure 1

Graphical Presentation of Overall Pattern



Yet the quality of the final response cannot be inferred from model performance alone.

3.2 Deep Learning

If your data are high dimensional, sequencial, spatial, multimodal, or nonlinear, deep learning can be useful. Vankayalapati and Banerjee (2026) categorize the contributions on Deep Learning under four main phases of SCRM: Identification of risk, Risk analysis, Risk mitigation and monitoring.

Recurrent and long short term memory networks for dealing with sequential data, convolutional architectures for pattern recognition, graph-based architectures for network relationships, and reinforcement learning for sequential decisions are explored in this literature.

While deep learning extends the amount of information that can be processed, it also sharpens the following concerns. Large data sets, substantial resources, ongoing monitoring and complex expertise are sometimes necessary for a complex model. They can also be hard to understand what their internal decision logic is.

The consequence is that if they are not intentionally designed, technical power and organizational usability can go counterproductive.

3.3 Reinforcement Learning and Adaptive Decision Systems

Forecasting is about what to expect Next, reinforcement learning is about what to do Next.

This distinction is of great significance for SCRM. The problems of Inventory Allocation, Supplier Selection, Recovery Planning, Production Scheduling, and Routing are sequential problems. One decision changes the state for the second decision to be made.

Vankayalapati and Banerjee (2026) elaborate upon deep reinforcement-learning and multi-agent strategies for mitigation, supplier allocation and post-disruption recovery. These systems are moving from descriptive or predictive use to prescriptive and more autonomous decision making.

Its potential is there, as is so are the governance questions. With AI increasingly making decisions, it's important for organisations to know when they can rely on AI, when they need human approval and how assessment or accountability for outcomes needs to be applied where they are dangerous or unwelcome.

3.4 Explainable Artificial Intelligence

Explainability has even greater relevance when AI-generated decisions impact highly consequential business decisions such as those regarding suppliers, inventory, production, transportation, or compliance.

The authors of Ferrara and Isgrò (2025) explicitly include EAI in the context of multicriteria decision-making in supply chain risk. Algorithmic transparency is also highlighted as a point of concern by John et al. (2025) in their comments on manufacturing supply chains.

The challenge to the management is simple. The risk score, however, does not necessarily mean that something needs to be done just because it's right based on statistics. A manager should be familiar with:

- identizing the variables that played a key role in making that prediction;
- whether or not the reaction is spontaneous and irreversible;
- if there is a tendency to use biased historical information;
- how big the change to the results is due to a change in assumptions—sensitivity;
- what alternatives there are to taking that action;

Explainability has meaning both technically and in terms of organizing. It can assist in model validation and also help to build upon informed trust.

3.5 AI Combined with IoT, Digital Twins, Blockchain, and Control Towers

The use of AI is not typically siloed. It is dependent on data-generating and data-sharing infrastructure.

In their recent study, Balasubramanian and Gurushankar (2020) pay attention to hardware-software integration, such as the use of IoT sensors, RFID tags, GPS gadgets, and AI analytical platforms. Continuous data acquisition, in essence, is the main part of those kinds of infrastructure. Sensors can convey information on the environment, motion, equipment status, or product quality and then AI processes those observations into a signal that is relevant to risk.

Tathed (2025) takes this logic further — via 'intelligent control towers' and 'digital twins'. A digital "twin" can include parts of the physical supply chain and prompt the evaluation of a variety of responses and scenarios in a computational environment without putting the physical network at risk.

A different perspective has been added by Oliveira et al. (2025), in which they review the AI technologies based on maturity and impact. This can be quite helpful, because while the applications themselves are technologically promising, they may not be sufficiently developed to become the basis for a marketable service, while other, perhaps less innovative, ideas may have already found wide application.

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When choosing technologies, therefore, it is not only important to assess the theoretical capabilities, but also readiness, reliability, cost of integration, extensibility, and anticipated organizational impact.

4. Review Methodology

4.1 Review Design

The research used in this study is the bounded systematic-integrative review.

Systematic is defined as the use of explicit eligibility rules, structured extraction, source verification, thematic coding, cross-study comparison and transparent synthesis. Integrative suggests a diverse body of evidence, ranging from empirical quantitative studies, application studies, systematic reviews, surveys, analytical frameworks, through to conceptual contributions. The word bounded must not be omitted. The a priori definition of the corpus was based on 23 publications supplied for the review. Therefore, a methodological mistake typical of reconstructed reviews, which consisted of reporting the number of database searches, screening counts or modified PRISMA flows, is avoided. By contrast, the review focuses on a much more containable question: What logical and practical inferences can be made on a systematic basis from the stated evidence corpus?

4.2 Review Corpus

The publications in the corpus span the years 2020–2026, most of which are from the year 2025. The sources cover:

- general AI applications in supply chain management;
- demand forecasting;
- supplier risk;
- disruption prediction;
- early-warning systems;
- proactive risk mitigation;
- explainable AI;
- digital twins and control towers;
- customs and supply-chain security;
- sustainable supply chains;
- manufacturing risk management;
- AI technology maturity;
- deep-learning applications;
- and firm-level empirical risk mitigation.

The included sources represent several types of evidence.

Table 1

Main Evidence Categories in the Review Corpus

Evidence category	Illustrative sources	Primary contribution
Systematic/review studies	Daios et al. (2025); Ghouati et al. (2025); Jahin et al. (2025); Senthil & Jenifer (2026); Teixeira et al. (2025); Vankayalapati & Banerjee (2026)	Mapping applications, methods, barriers and research gaps
Empirical firm-level evidence	Tian et al. (2025)	Tests whether AI is associated with reduced supply-chain risk and investigates mechanism
Forecasting/predictive studies	Bansal (2025); Hasan (2025); Huang (2025); Ngunjiri (2021)	Demand prediction, disruption analytics and early warning
Supplier and risk-control studies	Adesola et al. (2025); Yang et al. (2025)	Supplier management and multi-level risk mitigation
Explainability/human factors	Ferrara & Isgrò (2025); John et al. (2025)	Explainability, bias, transparency, human-AI collaboration

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Evidence category	Illustrative sources	Primary contribution
Integrated digital infrastructure	Balasubramanian & Gurushankar (2020); Tathed (2025)	IoT, RFID, sensors, digital twins and AI control
Technology evaluation	Oliveira et al. (2025)	Technology maturity and effect
Security/customs applications	Vijayakumar (2025)	Data-driven customs risk and security
Broader AI-SCM implementation	Larbi et al. (2025); Nawrin et al. (2025); Rahaman et al. (2025)	Adoption, optimization, disruption management and implementation

4.3 Eligibility Criteria

When a publication met the following conditions, it was kept:

1. It had been one of the 23 reviewers' built-in sources provided, and;
2. it was a substantive element involving Artificial Intelligence, Machine Learning, Deep Learning, Predictive Analytics or similar intelligent technologies;
3. it dealt with supply chains, logistics, sourcing, supplier management, customs or a specific activity in a supply chain;
4. it helped with the identification of risks, the risk assessment, the forecasting of risk under uncertainty, the risk mitigation, risk monitoring, resilience or risk disruption management; and
5. there is an adequate amount of source information to showcase how much the study contributed without making up data.

The differences in methodology of individual papers from the various publications did not exclude any paper. Evidence classification, instead of being baskets stuffed with children of the same age, was used as the approach to address heterogeneity.

4.4 Data Extraction

The following dimensions were analysed for each publication:

- year and publication type;
- supply-chain context;
- research objective;
- AI technique or technological architecture;
- SCRM function;
- data or evidence type;
- theoretical basis;
- reported contribution;
- organizational mechanism;
- implementation barrier;
- human or governance issue;
- limitation;
- and future research direction.

The extraction logic was intentionally changed to have a much wider scope than model-performance coding so that from the review the process of integrating AI capability into SCRM capability could be understood.

4.5 Evidence Synthesis

The studies were analysed in 4 steps.

First of all, functional coding was related with applications to risk identification, assessment, mitigation, and monitoring.

Secondly, capability coding studied the core functions of AI, such as sensing, prediction, classification, optimization, simulation, decision support and adaptive learning.

Thirdly, translation coding studied connections between the conditions of organization of AI output and practice. The recurring issues were those of data quality, technological maturity, readiness of the organization, transparency, managerial trust, human expertise, and governance.

Fourth, theory integration compared what had been identified from the various studies and created an explanatory framework that linked the AI capability, SCRM capability, and the dynamic supply-chain capabilities to the resilience.

Due to the diversity in methods, outcome measures, sectors, and ways the reviews were designed, there was no attempt at a meta-analysis. No pooling of numerical results was done on not compatible measures.

5. Findings

5.1 AI Is Reconfiguring Risk Identification From Periodic Inspection to Continuous Sensing

The traditional method of assessing risks through periodic inspections is changing to a continuous sensing approach with the advent of AI. The use of AI is revolutionizing the way risk is identified, moving beyond periodic inspections to a continuous sensing approach.

The first large-scale pattern is the change in time structure of the identification of risk.

In many cases, traditional risk assessment is conducted on a periodic basis. Suppliers are reviewed at regular intervals and based on the manager's observations of supplier performance, incidents in the past, compliance data, inventories, or operational reports. There is a lag time in the emergence of a weak signal and their recognising a weak signal as something to act upon.

The use of AI can reduce this delay.

In Balasubramanian and Gurushankar's (2020) architecture, the data continuously generated by the use of Iot sensor, RFID tags, GPS, and AI platforms are provided. Huang (2025) deals directly with machine-learning capabilities of early-warning systems. Daios et al. (2025) and Teixeira et al. (2025) reveal wider uses of AI that enhance information management throughout a supply chain.

The significance of AI here is not simply "automation." It is persistent sensing combined with pattern recognition.

Where relevant data are available, risk identification can become:

- continuous rather than episodic;
- multisource rather than isolated;
- predictive rather than exclusively descriptive;
- and network-oriented rather than confined to the focal firm.

However, this advantage depends on the integrity of the data-generation layer. Sensors can fail, data can be delayed, systems may use inconsistent definitions, and information-sharing restrictions can create blind spots. AI therefore does not remove informational risk; it changes its form.

5.2 Predictive Capability Is the Most Mature but Also the Most Easily Overinterpreted AI Contribution

Forecasting is one of the most established AI applications in the corpus.

Bansal (2025) and Ngunjiri (2021) have discussed about the machine learning and hybrid predictive analytics that are at the core of demand forecasting. In terms of the disruption management, predictive analytics are discussed by Hasan (2025), and machine-learning logic is used in the area of early-warning risk detection by Huang (2025).

Predictive capability is vital because it directly impacts nearly every major supply-chain decision, whether it's the uncertainty in demand, supplier performance, transportation, inventory and/or disruptions.

However, there is a critical misinterpretation to be noted in the literature, with the accuracy of the predictions considered as an organizational result.

The technical performance of a model is how well the model performs on a particular evaluation problem. Post-adoption performance of a supply chain relies on what happens once the prediction has been obtained.

This generates the "prediction-action gap."

For example:

Better forecast → planner gets the forecasted information → planner understands the information in his/her own way → inventory policy adjusts and shifts → procurement or production adjusts and changes accordingly → service/cost outcomes change.

All arrows indicate potential failure sites.

This could prove to be of little value if organisational response is restricted and is a technically better forecast. On the contrary, if a slight improvement is made in the analysis, but it influences a high cost decision when it is most appropriate, then it may be valuable to the business.

It is not the algorithm per se that is the correct domain of analysis, but the algorithm-in-organizational-process.

5.3 Supplier Risk Management Illustrates the Need to Combine Prediction and Actionability

The manager of suppliers is one of the most obvious examples of this.

The paper conducted by Adesola et al. (2025) explores the use of AI and machine learning in the field of supplier relationship management and risk mitigation. Other signals related to the supplier can be potentially integrated with AI to facilitate a classification or risk scoring.

Yet, classification is not the solution to supplier risk.

But when a model flags an important supplier as a risk, managers have a number of questions left to ponder:

- Is there alternate suppliers?
- Do production specification transfer well?
- What is meant by switching costs?
- Will diversification lead to quality issues?
- Does the company have any contractual leeway?
- Can the recommendation be explained to procurement managers?
- Is there an opportunity for the supplier to provide correct data?

It can give insights into why SCRM is not something that can be understood as just risk prediction. Complementary organisational resources are needed for effective mitigation.

5.4 AI Can Affect Supply Chain Risk Through Resource Allocation

Tian et al. (2025) presents the best corpus-based empirical approach relating to mechanisms.

They have theoretically grounded their study in the resource-based view and examine 1,367 A-share listed Chinese firms for 2008–2023. AI is revealed to serve as a risk-reducing tool and resource-allocation efficiency is seen as an instrumental mechanism.

This discovery is important for two reasons.

First, it short of a single algorithmic benchmark, offers a first-hand, firm-level proof.

Second, it implies that the actual value of AI can be rooted in part through information's facilitation of resource deployment.

AI can enhance the quality/speed of info that contributes to the decision on:

- inventory positioning;
- supplier allocation;
- production priorities;
- capital allocation;
- capacity deployment;
- and operational adjustments.

The presence of AI does not mean that it is simply a tool that "predicts risk" in this understanding. It is one resource that increases an organization's capacity in uncertainty to allocate other resources.

Thus, Tian et al. (2025) offer a valuable theoretical connection between the fields of computational AI research and organizational resilience research.

5.5 Deep Learning Extends AI Across the SCRM Lifecycle

Vankayalapati and Banerjee (2026) offer a systematic literature review of the use of deep-learning applications in risk identification, risk assessment, risk mitigation, and risk monitoring.

They have found that while similar architectures are useful for similar types of problem in risk management, there are not one or more perfect styles.

Support such as deep-learning applications:

- anomaly detection and disruption detection;
- sequential forecasting;
- supplier-risk assessment;
- adaptive order allocation;
- scenario generation;
- mitigation policies;
- recovery planning;
- and continuous monitoring.

AI's shift from information to information learning, with the use of reinforcement learning and multi-agent systems, is especially significant because it alters how reinforcement learning and multi-agent systems impact the role of AI in decision making.

This opens the door for other study areas.

The challenge is not just on predicting the accuracy of a model. When circumstances differ from training conditions, it is important to assess whether autonomous or semi-autonomous policies are still safe, robust and explainable and that they fulfil the organizational goals.

5.6 Digital Twins and Control Towers Move SCRM Toward Simulation-Based Resilience

Tathed (2025) highlights that posture 2 — Integrated AI control towers and digital-twin simulation are part of a tool belt for resilient supply chain management.

These technologies offer the opportunity to move risk management from a passive to an experimental model.

A digital depiction of the supply chain can enable managers to explore questions like:

- What are the implications if a key supplier is no longer available?
- What is required level of stock buffer to buffer a delay?
- Which other river stretch has the lowest impact down stream?
- When a capacity constraint occurs, to where will it spread?
- What mixtures of sourcing and inventory reaction options work best in each circumstance?

The attractiveness about simulation is when it links prediction to potential action.

But, simulated resilience is still model reliant. An inadequate digital twin of the actual supply network can give the false impression of analytical control. The more important the issues of validation, calibration, freshness of data, and scenario realism become, the more dependent on simulation the organizations are.

5.7 Technology Maturity Matters as Much as Technological Novelty

A framework to analyse the maturity and effect of AI technologies is introduced by Oliveira et al. (2025). They analyse 24 literature-review papers and 118 application papers and have categorised 90 AI technologies.

This contribution is particularly helpful for managerial interpretation.

New, creative ideas are often rewarded in research. Organizations require reliability.

A technologically sophisticated system can command academic interest if it is successful and new, but more similarly "mature" and also "simple" can be more appropriate for deployment.

The adoption of AI should thus consider two distinct aspects:

What potential improvements will the use of this technology create?

Technological maturity to what stage has the technology been developed that it is reliable for operation?

Combining it's not just novelty, it's more informative.

A technology that is very high impact but not very mature could be a good technology for experimentation.

A medium technology with some levels of maturity might be suitable for operational use.

Technically mature designs are not all economically viable for implementation as a low-effect technology, due to the integration costs.

5.8 Explainability Is a Risk-Control Mechanism, Not Merely a Technical Feature

Explainability is in the scope of multicriteria decision analysis to SCRM, as described by Ferrara and Isgrò (2025), and considered one of the main challenges for AI-driven manufacturing supply chains, as mentioned by John et al. (2025).

This literature implies that explainability should not be optional as a user experience feature of an interface.

It has at least four functions.

First, it facilitates verification, such as enabling users to access information about the reason for a prediction or recommendation.

Secondly, it facilitates trust calibration. People shouldn't disapprove or unconditionally approve of AI.

Third, it facilitates accountability, specifically when decisions impact the suppliers, employees, customers or regulated activities.

Fourth, it can facilitate organizational learning as the manager can compare the model's reasoning with domain knowledge.

There's an important difference between trust and calibrated trust. Do not necessarily strive to have a high trust. A manager who blindly goes along with an incorrect model can cause as much problems as a manager who not uses a true model.

The objective is proper dependence.

5.9 Human-AI Collaboration Remains an Underdeveloped Link

The term "human-AI collaboration" and "resistance to automation" is explicitly emphasized in John et al. (2025). Those same concerns are found in the general discussion on AI for supply chains (Daios et al., 2025; Nawrin et al., 2025).

In technically-oriented research this issue has been underestimated.

AI systems typically do not work alone in an organization. Planners interpret forecasts; risk scores affect procurement officers; optimization outputs are taken into account by logistics; early warnings lead to escalation; and automated decisions are part of accountability.

Manager(s) add context and may carry knowledge not contained in the data set. Algorithms can find patterns that managers are unable to discover by the manual inspection.

The relationship is thus one that is complementary and not substitutive.

The main question that needs to be answered is:

What should be automated, augmented and what should be done manually?

Low consequence decisions can be made with a lot of automation. In rare, consequential, ambiguous or ethically sensitive decisions, a greater level of human control may be warranted.

5.10 AI-Enabled SCRM Faces Persistent Data Problems

Data issues remain a challenge for AI-Enabled SCRM.

Almost all sophisticated AI functions are based on the availability of data and its quality.

One of the most challenging aspects of supply chains is that information is spread throughout separate organizations. The platforms, data standards, and governance models used by suppliers, manufacturers, and warehouses, customs agencies, logistics providers, distributors, and customers can differ.

The result can be:

- missing observations;
- inconsistent identifiers;
- delayed data;
- biased historical records;
- incomplete supplier visibility;
- incompatible systems;
- privacy concerns;

- ing and unwillingness to disclose sensitive business information.

John et al. (2025) mention data bias, whereas Balasubramanian and Gurushankar (2020) give more attention to the reliability of data acquisition through hardware. Similarly, Jahin et al. (2025) and Vankayalapati and Banerjee (2026) point out data-related constraints in AI-driven risk assessment.

A complex model that is trained on substandard or poor information cannot fix the information problem.

This gives rise to the fundamental principle:

AI readiness is preceded by Data readiness.

6. Cross-Study Synthesis

The literature can be summarized through the relationship between AI capability, SCRM function, organizational mechanism, and principal limitation.

Table 2

AI Capability and SCRM Translation

AI capability	Primary SCRM contribution	Organizational mechanism	Principal limitation
Machine-learning prediction	Forecasting and risk estimation	Earlier planning and resource adjustment	Data dependence and transferability
Early-warning analytics	Risk identification	Shorter recognition-to-response interval	False signals and information quality
Supplier-risk analytics	Assessment and sourcing support	Better supplier prioritization and diversification	Transparency and actionability
Deep learning	Complex pattern recognition	Improved analysis of sequential/high-dimensional data	Opacity and computational requirements
Reinforcement learning	Mitigation and adaptive control	Sequential optimization	Safety, validation and decision authority
IoT + AI	Continuous monitoring	Real-time visibility	Sensor reliability and integration
Digital twins	Scenario-based mitigation	Ex ante evaluation of alternatives	Model validity and synchronization
Explainable AI	Decision support and governance	Calibrated trust and accountability	Accuracy-explainability trade-offs
AI control towers	Network-level coordination	Integrated situational awareness	Integration cost and organizational complexity

The table is a good illustration of the conceptual flaws of considering AI as a single independent variable. AI is made up of diverse capabilities, which are implemented in distinct ways.

7. The AI-to-Resilience Translation Framework

The synthesis agrees to an integrative model having five successive layers and four key boundary conditions.

Layer 1: Data and Digital Infrastructure

The starting point of the framework is information environment.

The ability of AI relies on:

- data availability;
- quality;
- integration;
- timeliness;
- interoperability;
- sensing infrastructure;
- and governance.

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This layer is lacking otherwise sophisticated analytical models are poorly organized.

Layer 2: AI Analytical Capability

The second layer describes the contribution that AI enables the organization to make at the analytical level.

The evidence highlights four capabilities:

- Sensing — identifying significant patterns and irregularities.
- Prediction — estimating the need for things, delays, failure and disruption in the future.
- Optimization — comparing between various possible operational actions.
- Adaptive Learning — updating models/decision policies as conditions evolve.

Layer 3: AI-Enabled SCRM Process Capability

The results of the analysis are useful only as part of SCRM.

The following process capabilities relate to:

- risk identification;
- risk assessment;
- risk prioritization;
- mitigation;
- monitoring;
- response;
- and recovery.

This layer forms the most important link between the technical AI and the organizational results.

Layer 4: Dynamic Supply Chain Capability

Effective SCRM processes strengthen broader organizational capabilities:

- visibility;
- agility;
- flexibility;
- coordination;
- adaptability;
- and reconfiguration.

These capabilities explain how risk-management improvements become resilience.

Layer 5: Resilience and Performance Outcomes

The last layer focuses on resilience and performance outcomes.

Potential outcomes include:

- lower disruption exposure;
- faster response;
- better continuity;
- improved resource allocation;
- stronger recovery;
- reduced vulnerability;

Additionally, and more importantly, more reliable and efficient supply-chain performance.

It intentionally does not prescribe that all uses of AI are beneficial to all.

Boundary Conditions

The four conditions of the process of translation across layers are:

Data quality and technological maturity: Lack of quality or connecting data restricts analytical performance, while under-mature technologies pose deployment uncertainty.

Organizational readiness: The four factors of the application of AI are: analytical abilities, process redesign, managerial commitment and integration ability, and resources.

Explainability and human-AI collaboration: The output of the model needs to be interpreted, challenged, accepted, and translated into decisions.

Contextual uncertainty and governance: The focus is on governance and contextual uncertainty. Appropriateness of specific AI systems is affected by issues of regulation, cybersecurity, ethical requirements, characteristics of industries, type of risk and extent of disruption.

8. Research Propositions

Six propositions are put forward, based on the synthesis.

Proposition 1. AI's positive impact on supply chain risk management relies on the quality, timeliness, integration, and relevance of the data infrastructure it relies on for building and applying AI.

Proposition 2. AI analytical capability benefits supply chain resilience indirectly, by bolstering risk-identification, risk-assessment, risk-mitigation, and risk-monitoring capabilities, not necessarily by predictive technical performance.

Proposition 3. How AI powered SCRM affects resilience depends on its impact on the SCRM's dynamic supply chain attributes which include visibility, agility, adaptability and reconfiguration of resources.

Proposition 4. One of the key ways AI-driven information and prediction mitigate supply chain risk in firms is by enhancing resource-allocation efficiency.

Proposition 5. Explainability and effective human-AI collaboration (eHAC) enhances the translation of insight derived from the AI to appropriate organizational actions through improved calibrated trust, interpretability and accountability.

Proposition 6. The value of an AI technology to an organisation is closely linked to its technological impact and maturity as a technology, so more sophisticated algorithms do not necessarily result in more resilient solutions.

These propositions take pains to avoid formulas that involve random numbers. The evidence does not support the idea that a universal level of prediction accuracy will create business value.

9. Discussion

9.1 Moving Beyond the "AI Improves Supply Chains" Argument

The general sentiment that AI will enhance supply-chain decision-making has now become more than just a notion.

What is important is the better explanation of how improvement takes place.

The reviewed evidence suggests the following sequence:

Resilience is the result of the dynamic supply chain capability, which is a function of the AI analytical capability of the SCRM process, and this is derived from the data.

This is one structure that could overcome a critical problem found in sparse AI-SCM research. Technical study is typically an algorithm to a performance metric. The typical approach to management studies starts with the use of AI and concludes with the outcomes of the organization. This connection is often not developed between them.

The framework features that mechanism as its main principle.

9.2 Prediction Is an Input to Resilience, Not Resilience Itself

One of the common flaws in the way AI is talked about is that the idea of its predictive accuracy directly leading to business results.

That is not a complete logic.

If the prediction is accurate, it affords an opportunity to act.

The opportunity is worth if it leads to:

- timing;
- available alternatives;
- decision authority;
- organizational flexibility;
- resource availability;
- and implementation quality.

This is an important difference for research design. Going forward, the use of RMSE, classification accuracy, precision, recall, and/or other measures of the model's performance should no longer be interpreted as evidence of model resilience.

Operational metrics should be linked with technical metrics, like:

- decision lead time;
- inventory adjustment;
- supplier switching;
- disruption duration;
- recovery time;
- service continuity;
- financial loss;
- or resource-allocation efficiency.

9.3 The Firm-Level Evidence Changes the Theoretical Conversation

The new evidence from the firm level introduces an additional layer for addressing the theoretical conversation. The new firm-level evidence adds another layer to the theoretical discussion.

Importantly, these are not limited to an isolated model as is the case in most studies on AI and supply chain risk, but rather, they focus on a large scale of firm data, which is something that Tian et al. (2025) have done.

Their resource-allocation procedure proposes that AI may be specified as a strategic resource in the organization.

This reinforces the relevance of the resource based view.

But the value from AI will not last just because it's bought. Algorithms and available commercial software may be easily copied. It is the organizational system that is hard to copy:

- proprietary operational data;
- accumulated domain knowledge;
- integrated workflows;
- analytical talent;
- managerial routines;
- cross-functional coordination;
- and learning processes.

So, the competitive value could be the arrangement of complementary resources, not only the AI technology itself.

9.4 Human Judgment Should Be Endogenized Into AI-SCRM Theory

The opportunities for human involvement are frequently seen as being implementation after the technical model is designed.

That's, of course, too little.

Human decision makers determine:

- what data matter;
- what risks are acceptable;
- what recommendations are credible;
- how to handle exceptions;
- how competing objectives should be balanced.

Human judgment, then, must come in the middle of the causal model.

The only thing that's worse than a poorly functioning AI system is a well-functioning one used poorly. A moderately functioning system, carefully combined with the expertise of the humans, can add value.

This means that future theories ought to simulate the quality of the human-AI decisions, not just the accuracy of the AI decisions.

9.5 Explainability Should Be Treated as a Resilience Capability

Explainability is typically explained as a characteristic of responsible AI.

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However, it has a special role within SCRM as well.

Managers work with limited information and finite time when disruptions occur. Rather than being accepted, recommendations that are not understood may be rejected, just at the moment that swift action is needed.

Therefore, explainability can help to lessen decision friction.

It also lets an organisation know when one of the models is deviating from its behavior, as the operating environment has changed.

Therefore, explainable AI must be considered more than a moral restriction; it can be viewed as an operational resiliency instrument.

10. Theoretical Contributions

The review provides four theoretical contributions.

10.1 It Distinguishes Analytical Capability from Organizational Capability

AI creates sensing, prediction, optimization and adaptive-learning power. These capabilities are not resilience, unless they change organizational risk-management processes.

This difference is there to avoid using technology as a guaranteed performance.

10.2 It Integrates Resource-Based and Capability Perspectives

Tian et al. (2025) offer evidence of AI's potential to shape risk by managing resources, which aligns with its role as a strategic tool. However, broader evidence points to complementary capabilities like data integration, organisational learning and coordinated response as critical factors for value.

10.3 It Introduces the Prediction-to-Action Gap

The review reveals a disconnect in thinking between the improved quality of the model output and actual business value.

This translation process should be specifically explored in future research projects relating to AI-SCRM.

10.4 It Positions Human-AI Interaction as a Boundary Condition

The willingness to accept AI recommendations, their interpretability, managerial competence, and decision-making power influence the likelihood of proper implementation. These are not relevant to peripheral fears about the adoption of AI but are part of the explanation for its role in resilience.

11. Managerial Implications

Three implications are particularly important for managers.

11.1 Fix the Data Environment Before Buying More AI

Organizations frequently frame AI readiness as a software or talent problem.

The evidence suggests that data infrastructure comes first.

Managers should evaluate:

- completeness;
- consistency;
- timeliness;
- accessibility;
- interoperability;
- ownership;
- and governance

before selecting sophisticated models.

A high cost algorithm won't work consistently with bad structured information.

11.2 Evaluate Business Decisions, Not Just Model Accuracy

Technical metrics on their own do not constitute a measure of a model's success.

Managers should ask:

1. What will be decided that will impact on the prediction?
2. How much earlier can action be taken?
3. What are the financial or operational risks that are mitigated?

4. Is the organisation flexible enough for response?
5. What is the consequence of the failure to get the model right?

These questions translate AI evaluation to be a risk-management exercise.

11.3 Preserve Human Accountability for Consequential Decisions

When the problem is repetitive and not particularly important, it may be suitable to use autonomous optimization.

Decisions, such as supplier exclusion, emergency sourcing, large-scale inventory reallocations, compliance actions, and network reconfiguration, are made that carry more weight and will benefit from clear accountability.

The human touch doesn't imply that you have to do all of the work that the algorithm is already doing. It should involve being responsible for exceptions, judgment over ethics, context interpretation and consequential compromises.

12. Research Agenda

The synthesis identifies seven priorities.

12.1 Link Technical Metrics With Real Operational Outcomes

Researchers should connect model performance with disruption cost, recovery time, service continuity, inventory outcomes, decision speed, and other operational measures.

12.2 Conduct Longitudinal Organizational Studies

There is a significant advantage if enterprises are observed prior, during and after the AI implementation, for most AI-SCRM claims would be stronger.

12.3 Study Prediction-to-Action Mechanisms

We need research into the question of why certain AI directives are followed and others are not in organizations.

12.4 Test Human-AI Decision Configurations

There is a need to compare fully human, AI-assisted, human-supervised and highly-automated decision structures.

12.5 Expand Explainable AI Research

Further research should identify which types and intensities of explanation provide better decisions without simply making them more transparent.

12.6 Examine Model Robustness Under Regime Change

Frequently, the data generation process gets disrupted in the supply chain leading to data which does not match that which was used in training the models. Evaluation needs to be done for concept drift, rare events, cascading failures, and low data environments.

12.7 Move from Node Optimization to Network Resilience

Future studies should examine the impact on the system's level of resilience when locally sub-optimal decisions are made by the AI agent in different tiers of the interconnected supply chain.

13. Limitations

There are several very important limitations to this review that should be noted.

Firstly, the evidence base is a fixed number of 23 publications, predetermined in the interest of limiting the number of publications considered to be key. The sources are drawn from a variety of methodological and topical approaches, but the review should not be understood as being exhaustive of all AI-SCRM scholarship.

Secondly, the sheer over-representation of recent publications, in particular from 2025, makes it difficult to make comparisons with the past.

Thirdly, there is heterogeneous evidence. The methods, sectors, level of analysis, AI techniques and outcome measures across studies are very different. Without more standardised evidence, quantitative pooling would be inappropriate.

Fourthly, that a few of the papers included are reviews. Including them is helpful for the mapping of the intellectual landscape but will not make conceptual observations be equivalent to independent empirical observations.

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Fifth, it is a new technology field in which technological development is extremely rapid. Technological maturity, as well as generative AI, autonomous agents, deep reinforcement learning and explainability are likely to be subject to regular revisions.

These restrictions are not a hindrance to the synthesis. They set the standard for interpreting the results of its conclusions.

14. Conclusion

AI is transforming supply chain risk management. This allows organizations to detect, assess, anticipate and respond to uncertainty to a much greater degree than ever before, through machine learning, predictive analytics, deep learning, explainable AI, IoT monitoring, digital twins, control towers and reinforcement-learning systems.

However, the overarching finding of this review is intentionally more conservative than the prevailing idea that AI just "makes supply chains resilient."

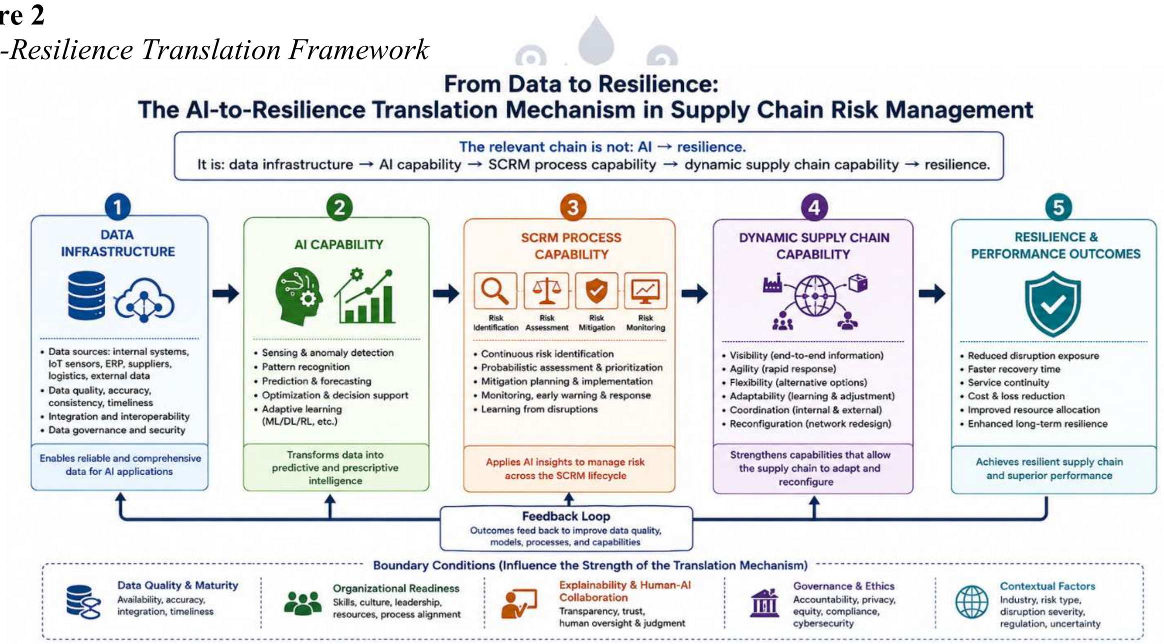
There is a creation of analytical capacity with AI.

Resilience only really comes to fruition when it is put into practice in terms of effective risk-management action within organizations.

The difference affects the way AI-SCRM will be taught.

Figure 2

AI-to-Resilience Translation Framework



In this chain, organizational readiness, technological maturity, explainability, governance and human judgement are all factors that influence the practical value of predictive intelligence.

There is some empirical evidence at the firm level that suggests one potential route by which AI decreases supply chain risk is through decreasing resource-allocation efficiency. Extensive studies on applications show that the forecast, supplier management, monitoring, early warning, simulation, and adaptive mitigation applications have significant possibilities. Meanwhile, studies on transparency and data bias, human-AI interaction and technological maturity reveal that more advanced AI is not necessarily superior AI.

The investigation should then proceed to a higher level of research, that is, to a different level from competitions based on predictive accuracy.

The question that needs to be addressed is what is the process for turning intelligence to action and action to resilience in an organization?

The transition from algorithms to translation mechanisms provides an actual basis for AI-based supply chain risk management theory and practice.

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