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The role of artificial intelligence in enhancing supply chain resilience: a structured narrative synthesis

Adel Aazami[1*], Amirhossein Hassani[2], Nadun Karunarathna[1] and Sebastian Kummer[1]

*Correspondence:
Adel Aazami
adel.aazami@wu.ac.at
[1]Department of Global Business and Trade, Institute for Transport and Logistics Management, Vienna University of Economics and Business, Vienna, Austria
[2]Department of Industrial Engineering, Sharif University of Technology, Tehran, Iran

Abstract

Global supply chains are increasingly exposed to large-scale, interconnected disruptions, making supply chain resilience (SCRES) a critical strategic priority. Artificial intelligence (AI) is widely discussed as supporting risk anticipation, visibility, and adaptive decision-making. This paper presents a structured narrative synthesis of 75 studies that met the inclusion criteria and were published from 2015 to 2025. The search was conducted through January 2026 in Emerald, Web of Science, and Google Scholar. Stage-specific retrieval counts, search logs, Web of Science index names, the Google Scholar bounding rule, reference-manager software, the number of screeners, and an agreement statistic were not retained and cannot be reconstructed. The paper is therefore not presented as a fully auditable systematic review or as a PRISMA 2020-compliant review. Thematic coding is combined with a limited descriptive bibliographic summary of the same corpus. Citation networks and keyword-evolution maps were not produced. The synthesis suggests that AI is discussed as supporting preparedness, agility, and recovery primarily through predictive analytics, machine learning, digital twins, and AI-enabled decision support systems. Relative to published AI-SCRES reviews, the unique increment is a conversion architecture rather than another catalog of tools. Agility and adaptability are the capability paths through which AI is associated with resilience outcomes. Governance maturity and digital readiness constrain whether those paths can operate. Five bounded contributions follow from that architecture, including a capability-stage mapping, the separation of the two paths from the two constraints, a treatment of explainable AI as a decision-relevant requirement, and a specification of sensing, seizing, and transforming as subprocesses that future work can test. The practical implication is that AI is more credibly treated as a governed socio-technical capability than as a stand-alone algorithmic solution.

Keywords Artificial intelligence, Supply chain resilience, Structured narrative synthesis, Predictive analytics, Decision support systems, Explainable artificial intelligence (XAI)

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1 Introduction

Global supply chains have become one of the defining infrastructures of the modern economy. They connect firms, suppliers, logistics providers, and customers across continents through dense networks of material flows, information exchange, and financial transactions [1]. This connectivity has enabled firms to source globally, specialize operations, and compete on cost and speed. At the same time, it has increased the complexity of supply networks and intensified interdependence among actors [2]. A disruption in one location can now propagate quickly across multiple tiers, regions, and industries [3].

For several decades, many supply chains have been designed around efficiency-oriented doctrines such as Just-in-Time (JIT) manufacturing and lean inventory management. These strategies have delivered clear operational benefits, including lower working capital requirements, reduced warehousing costs, and faster response to predictable market conditions [4]. Yet, the same strategies often reduce redundancy and remove buffers that historically absorbed shocks. When safety stock, spare capacity, and alternative sourcing options are minimized, the system can become more sensitive to volatility. As a result, the pursuit of efficiency can unintentionally weaken resilience.

This tension is increasingly visible in real-world events. The last decade, and especially the period after 2020, has shown how quickly disruptions can escalate from isolated incidents into widespread supply chain crises [5]. Earlier disruptions were often local and operational in nature, such as a fire at a production facility, a labor strike at a port, or a short-term transportation breakdown. In contrast, recent disruptions have taken on broader and more systemic forms. The COVID-19 pandemic constrained labor availability and restricted cross-border mobility, which exposed vulnerabilities in global manufacturing footprints and logistics capacity [5]. Geopolitical tensions and conflicts have contributed to trade restrictions, sanctions, and uncertainty in critical supply markets. In parallel, climate-related hazards such as floods, storms, heatwaves, and wildfires have increased the frequency and intensity of disruptions affecting production and transport routes. These developments illustrate a fundamental challenge: traditional approaches that rely heavily on stable patterns and historical precedents are not sufficient when supply chains face high-impact events that evolve rapidly and have complex spillover effects.

Within this context, the need for resilient supply chains has moved from a strategic preference to a core operational requirement. Firms are expected to maintain service levels, protect customer trust, and ensure continuity despite uncertainty. This expectation creates demand for approaches that can sense risk earlier, interpret weak signals, and support faster decisions under constrained conditions. The growing interest in Artificial Intelligence (AI) reflects this demand. AI has the potential to process high volumes of diverse data, generate actionable insight, and support more adaptive decision-making across the disruption lifecycle. This review paper is positioned within that motivation. It synthesizes research on how AI contributes to supply chain resilience, what evidence exists regarding its effectiveness, and what barriers and risks are reported when organizations attempt implementation.

The financial and reputational consequences of disruption are often severe. Stock-outs translate into lost sales and reduced customer confidence. Production stoppages lead to cascading delays and higher costs across the network. Supplier failures can force emergency procurement and quality compromises. In many sectors, even short interruptions can damage long-term contracts or trigger penalties. These outcomes underline why

resilience has become a central concept in supply chain scholarship and practice. Resilience is not simply about avoiding disruptions, because many disruptions cannot be fully prevented. Instead, resilience is about preparing for disruption, responding effectively when it occurs, and recovering in a way that sustains performance over time.

Supply chain resilience, frequently abbreviated as SCRES, is commonly understood as the ability of a supply chain to anticipate disruptions, respond to them, and recover from them while restoring operations to an acceptable performance level. In some cases, resilience also implies improvement after disruption, meaning that the system adapts and becomes better prepared for future shocks [6]. This definition emphasizes resilience as a dynamic capability rather than a fixed asset. It suggests that resilience is built through processes, coordination, visibility, and learning.

Several authors describe resilience using phases or stages that reflect how organizations manage disruptions over time [7]. provide a useful taxonomy that connects the stages of preparedness, response, recovery, and development to broader views of resilience, including engineering resilience, ecological resilience, and evolutionary resilience. Preparedness is associated with readiness and robustness. It includes actions taken before a disruption, such as diversifying suppliers, improving flexibility, building contingency plans, or holding strategic inventory. Robustness reflects the ability to absorb shocks without immediate failure. Flexibility reflects the ability to shift operations, sourcing, or production when conditions change.

Response is often discussed in terms of agility. Once a disruption occurs, organizations need timely and accurate information about inventory positions, supplier status, transportation capacity, and customer demand. They must also make decisions quickly under uncertainty. Recovery refers to the process of stabilizing and returning to operational targets. It often includes rerouting logistics flows, reallocating resources, adjusting production schedules, and managing volatility that may occur after the initial shock. Development is the longer-term stage in which organizations learn from disruption and implement structural or strategic changes to reduce exposure in the future. This developmental component aligns with the evolutionary view of resilience, where learning and adaptation are central outcomes [7].

Traditional supply chain risk management has generally emphasized two broad approaches. The first is historical data analysis, where organizations estimate risk based on past disruptions and known probability distributions. The second is redundancy, such as maintaining higher inventory, reserving extra capacity, or building backup arrangements [8]. These approaches remain relevant, but they have limitations that have become more visible in contemporary supply networks.

A key limitation is that many supply chains still lack true end-to-end visibility. Risk often emerges upstream, and early warning signals can be hidden across lower-tier suppliers. When systems are fragmented, and data is not integrated across partners, focal firms may not identify vulnerabilities until disruptions have already affected operations [9]. A second limitation concerns decision speed. Global supply chains generate massive volumes of data in real time through enterprise systems, logistics tracking platforms, sensors, and external information sources such as market indicators and news. Human-centric and rule-based systems struggle to process this data quickly enough to support timely decisions. This matters because disruptions can unfold rapidly, and response

windows are often short. In scenarios such as cyber incidents or flash floods, decision-making timelines are often measured in minutes rather than days [10].

A third limitation is that historically grounded models perform poorly when disruptions have limited precedent. Some events, such as pandemic-scale shutdowns or sudden geopolitical escalations, introduce conditions that do not resemble past patterns. Under such circumstances, organizations need adaptive and prescriptive capabilities that can generate options and recommend actions under uncertainty, rather than simply react using fixed playbooks [11]. These limitations help explain why AI is increasingly discussed as a potential enabler of resilience.

AI is increasingly used in supply chain management to support forecasting, monitoring, planning, and execution. In this review, AI refers to a set of technologies that include machine learning, deep learning, predictive analytics, prescriptive analytics, computer vision, digital twins, and robotic process automation (RPA) [12]. What unifies these technologies is their ability to process large and diverse datasets and to generate insight or action that supports decision-making. This capability is particularly relevant for resilience because resilience requires rapid sensing, interpretation, and coordinated response across complex networks.

AI can support resilience across the disruption lifecycle by strengthening preparedness, improving response, and enabling recovery and learning.

Preparation: readiness and robustness. AI can improve preparedness by detecting risk signals earlier and by producing more accurate forecasts. Machine learning and deep learning models can integrate internal operational data with external signals such as weather patterns, demand indicators, freight rates, customs data, and geopolitical information. By capturing these relationships, predictive analytics can improve forecasting accuracy for both demand and supply risks [13]. This supports more targeted and strategic forms of redundancy, where firms allocate buffers based on risk exposure rather than applying uniform safety stock. AI can also identify anomalies in transactional data, such as unusual order spikes, shipment delays, or unplanned downtime, which may indicate emerging disruption. Detecting these signals early can enable corrective action before disruption becomes widespread [8].

Response: visibility and agility. When disruption occurs, decision quality depends heavily on visibility and speed. AI can support real-time visibility by integrating data from Enterprise Resource Planning (ERP) systems, transportation management systems, warehouse systems, IoT sensors, and logistics tracking. When these data streams are combined, they can support an operational representation of the supply chain that improves situational awareness. In the literature, this is frequently discussed in relation to digital twins and data fusion. With improved visibility, prescriptive analytics can evaluate alternative response strategies across many constraints. For example, it can compare rerouting options, identify substitute suppliers, propose production resequencing, or rebalance inventory across nodes. The benefit is not only faster decision-making, but also more consistent evaluation of trade-offs under pressure.

Recovery: adaptability and learning. Recovery often involves stabilizing operations while managing administrative load and ongoing volatility. RPA can automate repetitive recovery-related tasks, such as updating purchase orders, processing documentation, issuing customer notifications, or supporting claims handling. By reducing administrative workload, RPA can free human decision-makers to focus on strategic

reconfiguration. Importantly, disruptions also generate new data that can be used for learning. AI models can be retrained based on disruption characteristics, the response actions taken, and the resulting outcomes. Over time, this can support adaptive improvement and reduce vulnerability to similar future disruptions.

Research on AI in supply chain management has expanded rapidly since the mid-2010s, and recent studies report applications across forecasting, inventory planning, logistics optimization, and automation. However, research that focuses specifically on supply chain resilience remains fragmented. Many studies are narrowly scoped, examining a single algorithm or tool applied to a single resilience activity, such as demand volatility forecasting or disruption detection. In contrast, broader frameworks that map a range of AI technologies across preparedness, response, recovery, and development are less common.

Another challenge is that evidence is uneven across contexts. While conceptual frameworks and simulation-based research are prevalent, empirical studies that measure outcomes in real organizational settings are comparatively limited. Implementation challenges are also reported inconsistently. These include data quality issues, integration complexity, shortages of specialized talent, governance concerns, and ethical issues such as bias and privacy risks. As a result, the current literature provides valuable insight but lacks consolidation. This creates the need for a structured review that synthesizes evidence, clarifies what is established, identifies gaps, and proposes coherent directions for future research.

For clarity, this review adopts a broad but structured definition of artificial intelligence, encompassing statistical learning, machine learning (ML), deep learning (DL), generative AI (GenAI), operations research and optimization (OR), symbolic AI, hybrid AI architectures, and decision-support system (DSS) infrastructures. A detailed taxonomy is provided in Sect. 2.3.

The aim of this synthesis is to examine how AI is discussed as contributing to supply chain resilience, with attention to applications, reported effectiveness, implementation challenges, and emerging research directions. The synthesis is guided by the following main research question:

How can AI tools enhance supply chain resilience in the contemporary business environment?

To address this question in a structured way, the synthesis also considers three supporting questions:

1. Which AI technologies and tools are most frequently associated in the literature with resilience across preparedness, response, and recovery?
2. What challenges and limitations are reported in implementing AI for resilience, and what strategies are proposed to address them?
3. How do AI applications support supply chain agility, adaptability, and innovation in disruption response?

The paper is positioned as a structured narrative synthesis of a fragmented evidence base rather than as a causal test of AI effects, and rather than as a fully auditable systematic review. While prior reviews address several of these elements individually, the reviewed literature does not appear to integrate them jointly into the conversion architecture developed in this study. Cluster-based syntheses inventory themes without separating

operative agility from strategic adaptability. Technique-specific reviews locate value in one analytics family. Implementation frameworks treat readiness as a single checkpoint. Empirical Covid-era maps and network-design reviews do not jointly specify explainable AI, governance maturity, and digital readiness as distinct conditions on realized resilience. The intended contributions are fivefold and remain bounded by the quality of the included literature. The synthesis maps AI technology families to disruption-lifecycle stages to avoid treating AI as a homogeneous construct. Thematic coding is complemented by a limited descriptive bibliographic summary of the same 75 studies that met the inclusion criteria. That summary is not a bibliometric network analysis. Agility and adaptability are specified as two capability paths through which AI is converted into realized resilience. Governance maturity is distinguished from digital readiness, and both are conceptualized as independently necessary constraints rather than as estimated moderators. Interpretable AI (XAI) is discussed as a decision-relevant requirement in high-stakes disruption settings, not as a peripheral interface preference. Dynamic capabilities theory is used to specify sensing, seizing, and transforming as AI-supported organizational processes that future empirical work can test. These propositions are synthesis-derived and are not estimated path coefficients.

Previous research has mostly used these theoretical stances separately, leading to disjointed explanations of resilience afforded by AI. By contrast, RBV mostly describes why AI might be a useful organizational resource, but it doesn't go into great detail about how that resource is operationalized in times of disruption. The governance factors that affect the acceptance and implementation of AI-supported judgments are largely ignored by dynamic capabilities theory, which describes capability development. However, although governance approaches address trust, accountability, and organizational legitimacy, they do not explain how technical resources provide adaptive capacity. By integrating these three viewpoints, this review proposes a cohesive explanatory mechanism linking achieved resilience outcomes to AI resources, organizational competence development, and governance conditions.

The remainder of the paper is organized as follows. Section 2 reviews the conceptual background and related work. Section 3 reports the search sources, inclusion rules, appraisal approach, and the limited descriptive bibliographic procedure, and states why a full PRISMA reconstruction is not possible. Section 4 presents the findings. Section 5 discusses the theoretical and practical meaning of the synthesis. Section 6 draws out managerial, policy, research, and operationalization implications. Section 7 concludes and incorporates limitations and a future research agenda.

2 Literature review

2.1 Supply chain resilience as a multi-stage capability

Supply chain resilience (SCRES) is most consistently treated in the literature as a dynamic capability that manifests across time, rather than as a single operational characteristic. A widely used definition frames SCRES as the ability of a supply chain to anticipate, respond to, and recover from disruptions, returning to stable performance and, in stronger forms, reaching a better state through learning and reconfiguration [6]. This definition is consequential because it pushes resilience research beyond static 'shock absorption' and toward an integrated view that includes preparedness routines, fast response coordination, recovery execution, and post-event adaptation.

A lifecycle framing is frequently used to operationalize SCRES because it enables researchers to connect resilience to concrete managerial and informational needs [7]. propose a structured taxonomy in which disruption management is organized into stages such as preparedness, response, recovery, and development, and link these stages to engineering, ecological, and evolutionary views of resilience. In this framing, preparedness is the pre-disruption stage that emphasizes the creation of readiness and the building of buffers and flexibility. Response emphasizes agility, visibility, and coordinated action under time pressure. Recovery concerns restoration and stabilization, including mitigation of secondary effects such as amplified demand variability and resource bottlenecks. Development captures the longer-horizon learning and redesign phase in which firms revise their operating logic, sourcing and network configuration, and decision routines based on disruption experience [7].

This multi-stage view also clarifies why resilience has become more difficult to maintain in contemporary global supply chains. Many supply networks are highly efficient but structurally fragile, because efficiency-oriented doctrines reduce redundancy and create tight coupling between nodes and tiers. When tightly coupled systems experience shocks, small failures can cascade rapidly. Moreover, modern disruptions are often characterized by speed, novelty, and multi-causality, which makes historically grounded risk approaches less effective and increases the value of real-time sensing and adaptive decision-making [10, 11]. End-to-end visibility limitations intensify this challenge because upstream risks frequently remain latent until they propagate to focal firms, at which point response windows are compressed [9]. In this environment, resilience becomes increasingly dependent on information-processing capability, orchestration speed, and institutional learning, rather than only on physical buffers.

Figure 1 presents the synthesis-derived conceptual model that organizes the remainder of the review. The figure is a schematic of proposed relationships among AI capability families, mediating organizational capabilities, resilience outcomes, and two boundary conditions. It is not a statistically estimated structural model and does not report path coefficients.

In the proposed architecture, agility and adaptability represent the organizational capability paths through which AI resources are converted into resilience outcomes. Agility captures the ability to sense and act rapidly within the existing supply chain configuration, whereas adaptability captures the ability to reconfigure structures and

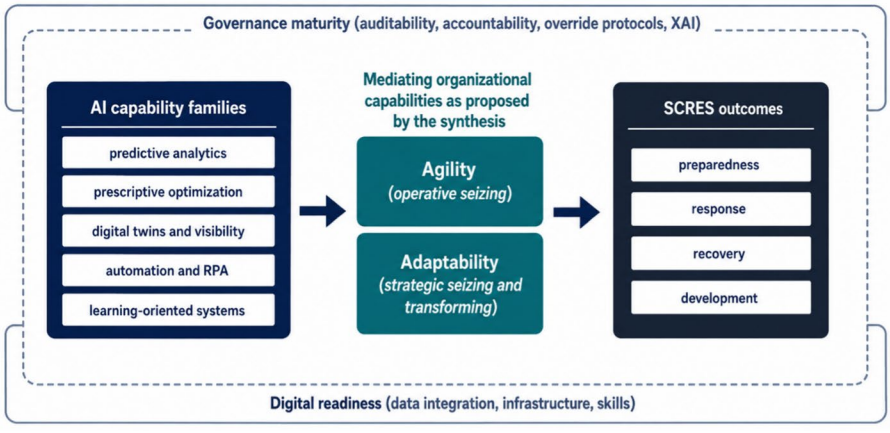

Fig. 1 Proposed synthesis-derived framework linking AI capability families to supply chain resilience

routines over a longer horizon. Digital readiness and governance maturity are treated differently: they are not additional capability paths, but boundary conditions that determine whether AI-enabled agility and adaptability can be effectively developed and operationalized. Digital readiness provides the technical and human foundation for AI deployment, while governance maturity provides the organizational conditions for accountable, trusted, and contestable use of AI-supported decisions.

Table 1 situates the present synthesis against closely related reviews. The comparison specifies what those reviews do not jointly provide. The reviewed AI-SCRES literature does not appear to jointly integrate these elements into a single conversion architecture, treat agility and adaptability as two conversion paths, or keep governance maturity distinct from digital readiness. The increment is in organizing architecture. The resulting framework is a conceptual model rather than a causal estimate.

2.2 Theoretical lenses for AI-enabled supply chain resilience

Research on AI-enabled resilience uses multiple theoretical perspectives to explain two recurring observations. First, similar AI technologies generate uneven outcomes across firms and sectors. Second, measured resilience improvements often depend on organizational and governance conditions rather than on algorithmic sophistication alone. Three lenses are especially useful for structuring this domain: the Resource-Based View (RBV), dynamic capabilities theory, and governance and trust-oriented perspectives rooted in adoption and institutional arguments.

2.2.1 Resource-based view: AI-related resources and resilience outcomes

RBV explains performance differences by emphasizing resources that are valuable, rare, difficult to imitate, and difficult to substitute [17]. Applied to AI-enabled resilience, RBV suggests that competitive advantage rarely comes from 'having AI' in a general sense, because algorithms, cloud services, and even pretrained models are increasingly

Table 1 Related works on AI-enabled supply chain resilience

Study	Focus	Design	Increment addressed in the present review
Zamani et al. (2022) [14]	AI and big data analytics for SCRES	Systematic review; four thematic clusters	Organizes four thematic clusters and calls for integration across sensing, decision-making, transparency, and learning. Does not specify agility and adaptability as two conversion paths, and does not treat governance maturity as a constraint distinct from digital readiness
Smyth et al. (2024) [15]	Prescriptive analytics and SCRES	Systematic review and research agenda	Locates prescriptive analytics value in structured decision support at the point of action. Does not extend the adoption argument across predictive and learning-oriented AI, and does not separate the two capability paths from the two constraints
Riad et al. (2024) [12]	Conceptual AI implementation for supply chain optimization and resilience	Conceptual framework	Treats implementation readiness and organizational fit as success factors. Does not separate governance maturity from digital readiness, and does not specify agility and adaptability as distinct conversion paths
Modgil et al. (2021) [16]	AI capabilities and SCRES in the Covid-19 setting	Empirical learning study; capability mapping	Provides a reasoning, prediction, perception, and interaction map in a Covid-19 learning setting. Is not a multi-database structured reading of the subsequent literature and does not theorize two constraints on conversion
Maharjan and Kato (2022) [3]	Resilient supply chain network design	Systematic review	Reviews resilient network design. Does not offer an AI capability, XAI, and governance synthesis, and does not specify conversion paths from AI to realized resilience

accessible. Instead, advantage tends to come from complementary resources that enable AI to operate reliably in resilience-critical conditions.

The literature increasingly locates these scarce resources in an organization's data assets and routines, including data quality, integration across functions and tiers, and the ability to sustain reliable real-time pipelines. These assets are not merely technical; they reflect organizational routines, governance discipline, and accumulated operational knowledge that are hard to replicate quickly [18]. From an RBV standpoint, AI contributes to resilience when it is embedded within a resource bundle that includes strong information architecture, skilled human capital, and cross-functional coordination routines. When these conditions are absent, AI initiatives can remain isolated pilots that do not translate into improved disruption performance.

RBV also clarifies why resilience outcomes may be path-dependent. Firms that historically invested in digital integration, standardized master data, and analytics governance are better positioned to extract value from AI because they can deploy models at scale and with acceptable reliability. In contrast, firms with fragmented systems and inconsistent data practices often face a high 'foundation cost' before AI can become operationally meaningful [19, 20]. This RBV framing aligns with the recurring empirical observation that the limiting factor in resilience-oriented AI is frequently not the availability of algorithms but the availability of reliable, integrated decision-grade data.

2.2.2 Dynamic capabilities: sensing, seizing, and transforming under disruption

Dynamic capabilities theory explains how firms adapt under turbulence through the capacity to sense opportunities and threats, seize them through rapid and coordinated action, and transform the organization's resource base when existing configurations no longer fit [21]. This lens is especially aligned with resilience because disruptions require rapid detection of weak signals, time-sensitive decisions under constraints, and learning-based reconfiguration.

In AI-enabled resilience, sensing is operationalized through continuous monitoring and forecasting systems that detect changes in demand, supply, logistics capacity, geopolitical conditions, and climate-related risk. Seizing occurs when AI supports fast evaluation of feasible actions, such as switching suppliers, rerouting shipments, reallocating inventory, or resequencing production. Transforming refers to longer-horizon changes, including redesign of network topology, multi-sourcing strategies, inventory policies, and governance routines that reduce vulnerability in future disruptions [18, 21]. This helps explain why the same AI tool can be associated with different resilience outcomes: the literature does not establish that AI causes resilience by itself, but it does indicate that AI can support the organizational ability to sense, decide, execute, and learn under turbulence.

The theoretical rationale for the proposed framework follows dynamic capabilities theory by treating sensing, seizing, and transforming as organizational processes that AI may support rather than replace. Sensing corresponds to foresight amplification through predictive analytics, anomaly detection, and signal integration. Seizing is specified at two levels: operative seizing through agility within the existing network configuration, and strategic seizing through adaptability in network redesign and planning logic. Transforming corresponds to longer-horizon learning, simulation-based reconfiguration, and institutionalization of revised routines. Resource-based reasoning explains why

AI models alone are not the scarce resource; integrated data, domain-literate human capital, and governance routines are the complementary resources that condition conversion. Governance and trust perspectives explain why technically capable systems may remain unused or indefensible under accountability pressure. The framework integrates these lenses by positioning agility and adaptability as conceptual conversion processes and governance maturity and digital readiness as independently necessary boundary conditions. This integration is a synthesis-derived theoretical proposition, not an estimated structural model. This distinction is theoretically motivated by the different temporal and organizational demands of resilience: agility concerns the rapid deployment of existing capabilities within the current supply chain configuration, whereas adaptability concerns the longer-term renewal and reconfiguration of that configuration. Separating these pathways, therefore, allows the framework to distinguish between responding effectively to a disruption and learning to reduce vulnerability to future disruptions.

2.2.3 Governance, trust, and technology acceptance as enabling conditions

A third theoretical strand arises because resilience decisions are high-stakes and accountability-intensive. Adoption-oriented and institutional arguments indicate that perceived usefulness, trust, auditability, and legitimacy shape whether managers rely on algorithmic recommendations under pressure [22–24]. The operational definitions of governance maturity, XAI, and digital readiness used in the remainder of the paper are stated once in Sect. 2.5 and are not restated at length here.

2.3 Taxonomy of AI technologies relevant to supply chain resilience

AI in supply chain resilience is best treated as a set of technology families that differ in data requirements, decision roles, and integration depth. The capability-stage mapping used in this synthesis covers predictive AI, prescriptive and optimization analytics, digital twins and Internet of Things (IoT) visibility systems, automation such as robotic process automation (RPA), learning-oriented systems, and AI-enabled decision support [12, 25]. Each family is summarised below; the detailed mapping of decision role, resilience stage, and illustrative methods is recorded in Appendix Table 15 rather than restated as a long technical taxonomy in the main text.

2.3.1 Predictive AI for preparedness and risk sensing

In the preparedness stage, predictive AI, including machine learning and deep learning, is discussed as supporting earlier risk sensing and more targeted buffering by combining internal operational data with external signals and by flagging anomalies in lead times and order streams [26–28]. The literature associates this family with readiness and robustness, not with an automatic improvement in every disruption regime.

2.3.2 Prescriptive and optimization AI for response decisions

In the response stage, prescriptive and optimization-oriented AI is discussed as evaluating constrained action sets (rerouting, supplier switching, inventory reallocation) more quickly than siloed local planning [12]. The literature links this family to agility because it is described as reducing decision latency when disruptions propagate across tiers.

2.3.3 Digital twins and real-time visibility for agility

Digital twins are framed as a near-real-time representation of supply chain states that can integrate enterprise, logistics, and IoT streams and support what-if evaluation when connected to prescriptive engines [12, 29]. Their reported resilience role is to connect situational awareness to action selection rather than to stop at monitoring dashboards.

2.3.4 Automation technologies for recovery execution

In recovery, RPA is positioned as a pragmatic tool for shortening cycle time on rule-structured administrative workflows such as reissuing orders and updating documentation [24, 30]. Compared with high-variance predictive tasks, these workflows are often described as easier to govern because they already exist as procedures.

2.3.5 Learning-oriented AI for adaptation and development

Learning-oriented AI is discussed as supporting the development stage by retraining on disruption data and by exploring alternative network structures [18]. Because disruption observations are sparse and heterogeneous, the same literature emphasises incident logging and data governance as preconditions of that learning, which is why those conditions are treated in Sect. 2.5 rather than as properties of the algorithm itself.

2.3.6 AI-enabled decision support systems for supply chain resilience

Decision support systems (DSS) provide the socio-technical bridge between analytical insight and managerial action [31, 32]. In this synthesis, AI is treated as expanding DSS capability rather than as replacing DSS: predictive models support early warning, prescriptive engines generate constrained options, and explainability is discussed as an enabling condition for accountable use [15, 33–35]. The DSS perspective, therefore, locates AI-enabled resilience in workflows that integrate data, present explanations, and record overrides, rather than in isolated predictive accuracy.

2.3.7 An alternative technical taxonomy of AI for supply chain resilience

An alternative technical classification of the same literature (statistical learning, machine learning, deep learning, generative AI, operations research, symbolic AI, hybrid architectures, and DSS infrastructure) is complementary to the capability-stage mapping. Neither classification is used as a scored coding scheme. Appendix Table 15 records the capability-stage mapping used for synthesis.

2.4 Linking AI to resilience dimensions through capabilities

A recurring synthesis across the AI-SCRES literature is that AI is associated with resilience primarily through improvements in agility, adaptability, and innovation, which then map onto preparedness, response, recovery, and development stages. Those improvements are treated as conversion paths rather than as automatic by-products of installing a model. AI produces signals and recommended actions. Resilience is a realized operational outcome. The literature indicates that the outcome appears when organizations convert those signals into coordinated action inside the current network and, over a longer horizon, into a redesigned network.

Agility is the operational capability to act quickly and coherently during disruptions. AI strengthens agility through a combination of real-time sensing, integrated visibility,

and prescriptive decision support. When the supply chain can interpret signals and evaluate options faster, it reduces downtime and limits cascading effects [21]. Digital twin infrastructures and prescriptive engines are especially aligned with this function because they connect current-state awareness to action selection.

Adaptability is the longer-term capability to change the system's structure, not just operate faster within existing structures. It is reflected in network redesign, diversification strategies, and revised planning logics that account for persistent uncertainty. The literature often links adaptability to simulation-based planning, digital twin experimentation, and learning loops that reveal structural vulnerabilities and support redesign choices [21, 36].

Innovation captures changes in routines and architectures that embed resilience earlier in decision processes and designs. This includes new governance routines, new data-sharing and integration approaches, and more proactive embedding of risk considerations in procurement, product design, and supplier management. In this pathway, AI drives resilience by accelerating digital transformation and enabling new operating models, not only by improving local operational decisions [16].

This capability-based framing also explains uneven empirical findings and implementation outcomes. AI systems can exist without producing resilience if they remain detached from operational routines, if decision-makers do not trust outputs, or if organizational processes cannot execute recommendations quickly. Conversely, relatively modest AI tools can produce strong resilience effects when embedded in mature routines and supported by reliable data and governance. That pattern is why later sections treat digital readiness and governance maturity as constraints on the pathway rather than as further mediators sitting on it.

2.5 Boundary conditions: digital maturity, data foundations, and governance

The literature consistently indicates that AI-enabled resilience is conditional. Two constraints dominate, and they are not interchangeable. Digital readiness, also discussed as digital maturity, refers to the technical and human feasibility of deploying AI. It comprises integrated data architecture, interoperable systems, scalable infrastructure, and skills spanning analytics and supply chain domain literacy [19, 20]. Governance maturity refers to the institutional feasibility of using AI under accountability pressure. It comprises audit trails, role clarity, override and escalation protocols, ethical criteria for allocation under scarcity, and explainability sufficient for contestable decisions [22–24]. Digital readiness without governance can produce technically capable systems that remain unused or indefensible during disruption. Governance without digital readiness can produce accountable procedures around models that cannot be fed timely, reliable data. The two constructs are independently necessary constraints rather than a single readiness index. They are constraints because they do not transmit AI effects. They determine whether the agility and adaptability paths can operate at all.

As defined above, digital readiness is the feasibility condition that allows AI tools to move from isolated prototypes to operational resilience systems. Low-readiness environments suffer from delayed or inconsistent data feeds, fragmented master data, and weak cross-functional integration, all of which degrade model reliability [19, 20]. The construct is not restated in later sections except where a new implication is drawn.

The resilience domain also faces a data paradox. Disruptions are precisely the events where AI could add the most value, but disruptive events are often rare, heterogeneous, and poorly documented, which creates sparse training data and weak generalization for extreme scenarios [25, 37]. This intensifies the need for systematic incident logging, shared taxonomies, and data-sharing mechanisms across tiers. Without these foundations, AI systems may perform well during stable periods but fail when they enter the non-linear regime that characterizes major disruptions.

As defined above, governance maturity is the institutional condition for using AI under accountability pressure. Without auditability, role clarity, and contestable explanations, AI may remain technically capable but unused, or may be used inconsistently, at the moment when disruptions require rapid action [22–24]. Later sections refer back to this definition rather than repeating it.

Taken together, these constraints align resource-based and dynamic-capabilities logic. AI becomes a resilience capability only when embedded in organizational resources that are difficult to replicate quickly, including digital maturity, integrated data, skilled teams, and governance routines, and when it strengthens sensing, seizing, and transforming processes under turbulence [17, 21]. This explains why the literature increasingly treats AI as a component of a broader resilience system rather than as a stand-alone solution.

The literature indicates a potential conditional pathway in which XAI supports interpretability, trust, and alignment with governance. When AI outputs are sufficiently transparent to be interrogated, organizations are better able to incorporate them into sensing, seizing, and transforming routines. This is a synthesis proposition, not an estimated moderation effect.

3 Methods

3.1 Review design and protocol

3.1.1 Type of review and justification of the design

This study employs a structured narrative synthesis based on a systematic search and staged study-selection process. Given that complete execution-level search and screening records were not retained, the review is not presented as a fully auditable systematic literature review or as a PRISMA 2020-compliant review [38, 39]. The objective was to provide a transparent and structured synthesis of the available evidence rather than to reconstruct unobserved identification and screening statistics. Accordingly, numerical counts not retained in the original review records are neither estimated nor reconstructed retrospectively. Reconstruction of the original identification statistics is not possible. Exact per-database retrieval totals, query-level search dates, full field-limited syntax as executed in each source, Web of Science index names, the Google Scholar bounding rule (pages screened, sort order, export method), reference-manager software, the duplicate matching rule, the number of screeners, and an agreement statistic were not retained in the review archive. Those quantities are therefore not reported and are not estimated. The confirmed element of the evidence base is the included set of 75 studies that met the inclusion criteria. A staged identification-screening-eligibility-inclusion sequence is used only as an organizing logic for describing how that set was assembled [40].

The objective of the design was to synthesize research that explicitly links (1) AI technologies or AI-enabled analytics, (2) supply chain or logistics contexts, and (3)

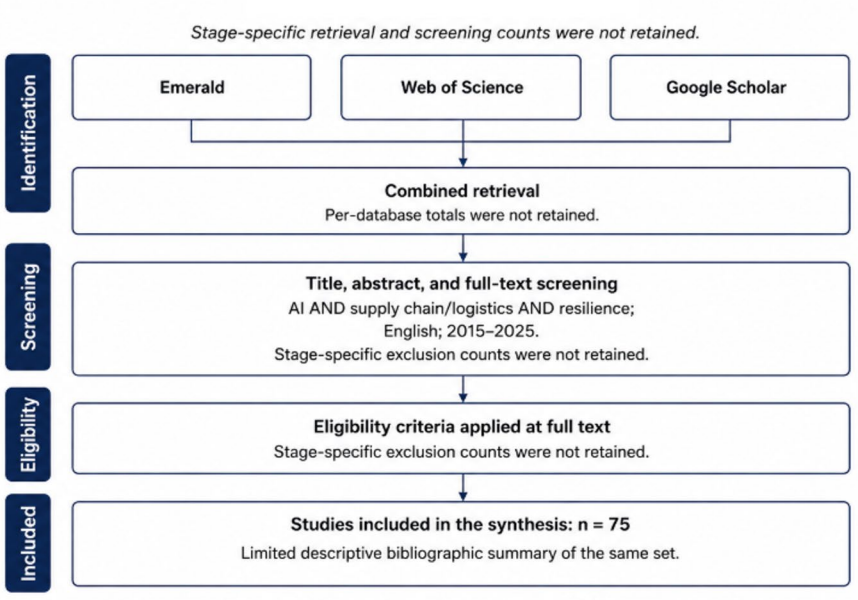

Fig. 2 Identification and inclusion pathway for the structured narrative synthesis. The pathway summarizes the sources searched, screening stages, eligibility assessment, and confirmed final evidence base ($n = 75$). Numerical retrieval, duplicate removal, and screening counts were not retained in the original review records and are therefore not reconstructed

Table 2 Core search-concept clusters and Boolean keywords

Cluster	Core concept	Keywords (with truncation and synonyms)
A: Supply Chain	The operational context	'supply chain' OR 'logistics' OR 'operations management' OR 'supply network'
B: Technology (AI)	The intervention	'Artificial Intelligence' OR 'AI' OR 'Machine Learning' OR 'ML' OR 'Deep Learning' OR 'DL' OR 'Predictive Analytic*' OR 'Automation' OR 'Digital Twin*'
C: Resilience	The desired outcome	'resilience' OR 'resiliency' OR 'robustness' OR 'agility' OR 'adaptability' OR 'risk mitigation' OR 'disruption management'

resilience-related outcomes such as preparedness, agility, or response, recovery, robustness, and adaptation [38, 39]. Because identification counts cannot be audited, the paper does not claim that the 75-study set is a complete census of the field.

3.1.2 Guiding principles and reporting

To improve transparency, Fig. 2 presents the identification and inclusion pathway used in the review. The figure summarizes the sources searched, the sequential screening logic, the eligibility assessment, and the confirmed final evidence base of 75 included studies. Because numerical retrieval and screening counts were not retained in the original review records, these values are not reconstructed or displayed. The figure is therefore intended as a methodological process map rather than a PRISMA 2020 flow diagram.

Accordingly, we do not claim compliance with PRISMA 2020. Instead, PRISMA principles are used only as a reporting-oriented reference for describing the stages of identification, screening, eligibility assessment, and inclusion. The honest unit of reporting is the included corpus ($n = 75$), together with the Boolean concept clusters in Table 2 and the eligibility rules in Sect. 3.4.

3.1.3 Research scope and context

The review focused on literature published from January 2015 through December 2025. The search was conducted through January 2026 to capture items with a 2025 publication year that were indexed at the time of the search. Studies dated 2026 were not eligible. This scope was selected to capture the period during which advanced AI methods became increasingly prominent in applied supply chain contexts and when major global disruption events accelerated scholarly and practical interest in resilience [39].

3.2 Comprehensive search strategy

A search strategy was developed to maximize coverage while maintaining specificity. The design emphasized three foundations: source selection, keyword construction, and Boolean logic. This approach is consistent with guidance on building search strategies for emerging technologies where terminology and indexing practices vary across fields [41]. It is not presented as a fully replicable multi-database protocol because the executed logs listed in Sect. 3.1.1 were not retained.

3.2.1 Database and source selection

The second was Web of Science, chosen because it supports structured searching of work in technology, operations research, and management. The specific Web of Science index(es) used during the original search was not retained in the review archive and is therefore not retrospectively inferred. The third was Google Scholar, used to broaden the retrieval of conference papers, highly cited working papers, and applied outputs that are not always visible in subscription databases. The Google Scholar procedure (sort order, number of result pages screened, export method, and any date or citation filter) was not retained as a replicable log. Google Scholar is therefore treated as a supplementary source, not as a fully parameterized database search. Its role was primarily to broaden the identification of potentially relevant literature that might not have been captured through the structured database searches.

The search scope was intentionally extended beyond journal articles to include case studies and industry reports where they contained sufficient methodological detail. This choice was made because AI implementation evidence, especially around adoption barriers and organizational constraints, is sometimes documented more explicitly in applied sources than in purely technical academic publications. The inclusion of these sources, therefore, served the practical goal of identifying real-world implementation insights alongside conceptual and simulation evidence [41].

3.2.2 Keyword construction and Boolean search string

The search query was structured using Boolean logic (AND/OR) to combine three concept clusters aligned with the research questions: (A) supply chain context, (B) AI technology, and (C) resilience outcomes [41].

The supply chain cluster included: supply chain OR logistics OR operations management OR supply network. The technology (AI) cluster included: Artificial Intelligence OR AI OR Machine Learning OR ML OR Deep Learning OR DL OR Predictive Analytic* OR Automation OR Digital Twin*. The resilience cluster included: resilience OR resiliency OR robustness OR agility OR adaptability OR risk mitigation OR disruption

management. The asterisk wildcard was used to capture variations (for example, Analytic* capturing analytics and analytical).

The final Boolean string applied primarily to titles, abstracts, and keywords (where supported) in Emerald and Web of Science was:

(supply chain OR logistics) AND (AI OR Machine Learning OR Predictive Analytics) AND (resilience OR agility OR disruption management).*

This formulation was intended to filter for studies in which AI technologies are not merely mentioned but are central to the investigation and are explicitly tied to resilience-related outcomes [41]. The Boolean formulation reported here represents the search formulation retained in the review documentation; database-specific field syntax and execution parameters are not retrospectively reconstructed where they were not retained.

3.3 Study selection and screening process

Study selection followed four sequential stages: (1) identification of potentially relevant records through the selected sources; (2) removal of duplicate records; (3) title and abstract screening; and (4) full-text eligibility assessment. Studies were retained for the final synthesis only when they satisfied the predefined inclusion criteria [38, 40]. Because numerical records from the original identification and screening stages were not retained, the number of records at each intermediate stage is not reconstructed.

3.3.1 Stage 1: initial retrieval and duplicate removal

The three selected sources were searched using the retained search concepts and, where applicable, Boolean formulation. Retrieved records were exported into a reference-management workflow, and duplicates were removed before title and abstract screening. The specific software, the matching rule (for example, DOI versus title-author-year), and the resulting duplicate count were not retained and are not reconstructed.

3.3.2 Stage 2: title and abstract screening

A rapid screening of titles and abstracts was then performed. The purpose of this stage was to test whether a study presented a clear linkage between three required elements: AI (or AI-related technologies), a supply chain/logistics context, and resilience/risk/disruption outcomes. Studies were retained when the abstract and title indicated that AI was applied in a supply chain setting to address disruption risk, resilience, or related performance outcomes. Studies were excluded if they discussed AI outside supply chain contexts or addressed resilience and disruption topics without a substantive AI component.

3.3.3 Stage 3: full-text assessment

Where uncertainty arose during screening, eligibility was revisited against the inclusion and exclusion rules until a consistent determination was reached [42]. The original review archive does not retain sufficient information to establish whether screening was conducted independently by multiple reviewers or to calculate an inter-reviewer agreement statistic. We therefore do not retrospectively assign a number of reviewers or report an agreement statistic that cannot be verified. In summary, Sect. 3.3 outlines the

screening logic and inclusion rules that guided identification of the included set; it does not reconstruct a personnel protocol that was not retained.

3.4 Inclusion and exclusion criteria

The inclusion and exclusion criteria were applied during the full-text assessment to ensure both relevance and a minimum level of evidence quality. The criteria were defined and used as strict filters to prevent scope drift and to ensure the final corpus supported credible synthesis [43].

3.4.1 Inclusion criteria

Studies were included when they satisfied all of the following criteria [43]:

- addressed an artificial intelligence technology, an AI-enabled method, or an AI-related analytical capability;
- considered a supply chain, logistics, or closely related operations context;
- explicitly addressed resilience, robustness, agility, adaptability, disruption, risk mitigation, preparedness, response, or recovery;
- were published between 2015 and 2025;
- were available in English; and.
- provided sufficient methodological or conceptual information to support structured appraisal and synthesis.

Eligible publication types included peer-reviewed journal articles, peer-reviewed conference papers, doctoral dissertations, and methodologically informative industry or government reports.

3.4.2 Exclusion criteria

Studies were excluded when they [43]:

- focused on non-AI technologies without a substantive AI component;
- addressed AI without a supply chain or logistics context;
- addressed supply chain resilience or disruption without a substantive AI application;
- fell outside the 2015–2025 publication window;
- were not available in English; or.
- lacked sufficient methodological or conceptual information to support appraisal and synthesis.

3.5 Quality assessment and critical appraisal

To ensure that synthesis conclusions were grounded in dependable evidence, all included studies underwent a structured critical appraisal procedure. The goal was not to impose a single 'best method' standard across diverse study types, but to confirm that each study's design, assumptions, and conclusions were sufficiently transparent to support interpretation [43].

3.5.1 Qualitative critical appraisal framework

The appraisal was qualitative and JBI-informed rather than a formal administration of a named JBI checklist with numerical scoring [44]. Given the heterogeneity of the included evidence base, the appraisal focused on five dimensions: (1) clarity of objectives; (2)

methodological adequacy and fit between the research approach and the stated objective; (3) validity and appropriateness of the data or evidence supporting the study; (4) transparency of the AI model, analytical procedure, or relevant assumptions; and (5) clarity of findings relative to the evidence presented [43, 44].

More specifically, the qualitative appraisal considered whether each study clearly stated its research objective or question; whether the selected methodological approach was appropriate for addressing that objective or question; whether the data, evidence base, assumptions, or other empirical or analytical material were sufficiently credible and appropriate for the claims made; whether the AI model, analytical procedure, or relevant assumptions were described with sufficient transparency to support interpretation; and whether the reported findings and conclusions were adequately aligned with the evidence, analysis, or argument presented. These dimensions were considered qualitatively across the included studies and were used to inform the interpretation and weighting of evidence. Item-level wording from a specific JBI instrument, binary or ordinal scores, a maximum score, numerical thresholds, the number of appraisers, and a formal disagreement-resolution procedure were not retained in the original review archive and are therefore not retrospectively reconstructed.

Evidence-weight labels used in the synthesis tables were defined as follows. High denotes comparatively strong methodological transparency, empirical grounding, and/or clear alignment between the study design and the evidence supporting its reported findings. Medium denotes adequate reporting for synthesis with residual design limitations. Low denotes limited methodological transparency or thin empirical grounding, so that the study informs mapping but is not treated as strong corroboration. Limited support denotes sparse empirical support for the specific claimed mechanism, for example, evidence based mainly on a conceptual argument or a single illustrative case. These labels guided cautious interpretation and weighting in the thematic synthesis; they are not JBI grades or numeric quality scores.

3.5.2 Risk of bias mitigation

Rather than removing every study with methodological limitations, the synthesis addressed the risk of bias through qualitative evidence weighting using the High, Medium, Low, and Limited support descriptors defined above. Studies characterized by unclear methods, limited methodological transparency, unsupported claims, weak empirical grounding, or non-representative evidence were interpreted cautiously and were not treated as strong corroboration. Studies with comparatively strong methodological transparency, adequate empirical grounding, and clear alignment between the study design and the evidence supporting their findings were given greater interpretive weight [43]. Where a specific claimed mechanism was supported mainly by conceptual reasoning or a single illustrative case, the evidence was described as having Limited support.

This approach preserved coverage of the emerging evidence base while reducing the risk that conclusions would be driven disproportionately by the weakest reports. The qualitative evidence-weighting procedure was used to moderate interpretation and support the thematic synthesis; it does not substitute for a numerical quality score, a formal JBI grade, or a score-based risk-of-bias assessment.

3.6 Data extraction and coding

After forming the final eligible set of studies, a structured data extraction process was applied to capture all information needed to answer the research questions and to support both descriptive mapping and thematic synthesis [43].

3.6.1 Extraction protocol

The extraction protocol captured bibliographic identification (authors, year, journal/source, and, where available, country context), study design (for example, case study, simulation, survey, conceptual paper, or review), and the specific AI tools examined. The extracted AI tool categories included methods such as RNN, CNN, regression-based learning, RPA, computer vision, and digital twins. In parallel, each study was coded for which resilience dimension it addressed (preparedness, agility/response, recovery, adaptability), and its key findings on AI's effectiveness or impact on SCRES. Finally, the extraction captured barriers and limitations described by the studies, including data quality constraints, culture and change barriers, cost, skill shortages, and ethical considerations [43].

3.6.2 Coding and categorization

The extracted qualitative data, especially on AI technology and the resilience dimension, were then coded using iterative thematic categorization. Initial codes (for example, 'AI for demand forecasting') were created and later consolidated into broader categories (for example, 'proactive risk sensing'). This iterative process supported systematic comparison across heterogeneous studies and enabled the synthesis phase to aggregate patterns rather than relying on isolated examples [43].

The overall methodological process is illustrated in Fig. 3, which is placed after this description. The figure summarizes sequential stages: scope and search, screening against the inclusion rules, extraction and qualitative appraisal, thematic synthesis, limited descriptive bibliographic mapping of the included corpus, and reporting. The figure is a process map, not a count diagram.

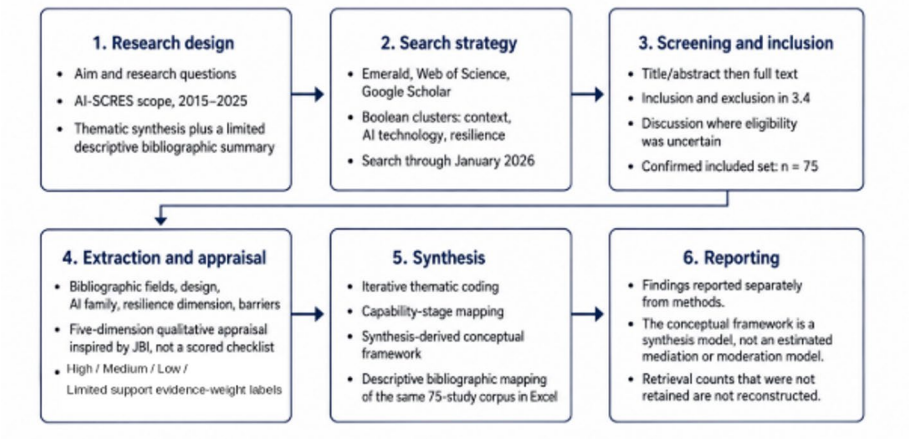

Fig. 3 Review process, from design and search through screening, extraction, qualitative appraisal, thematic synthesis, and limited descriptive bibliographic mapping of the included set ($n = 75$)

3.7 Data synthesis and framework development

The synthesis stage integrated the extracted and appraised evidence and served as the basis for generating the review's conceptual framework. The overarching purpose was to move from descriptive mapping of the AI–SCRES literature to a structured explanation of how AI capabilities relate to resilience outcomes and where implementation constraints intervene [43].

3.7.1 Thematic synthesis

The primary synthesis method was thematic analysis, selected because the evidence base contains mixed study types and is not suitable for statistical meta-analysis. Thematic analysis supports the identification of recurring mechanisms, relationships, and tensions across heterogeneous publications [43]. The synthesis logic was organized to align with the review's sub-questions. First, it mapped AI tools to resilience outcomes across the stages of preparedness, response, and recovery by identifying which technologies appeared most frequently and which resilience objectives they addressed. Second, it synthesized implementation challenges and limitations (technological, organizational, and ethical). Third, it consolidated findings about how AI supports higher-order resilience capabilities such as agility, adaptability, and innovation [43].

3.7.2 Framework development

Framework development was treated as the structured output of synthesis rather than as a purely speculative model. The framework integrates the thematic findings into an organized representation of how organizations can use AI capabilities to progress from basic robustness toward more advanced resilience forms that include learning and adaptation [43]. The framework was developed to be interpretable both academically (as a contribution that consolidates fragmented findings into a coherent logic) and managerially (as a mapping tool linking AI investments to resilience objectives).

3.8 Limited descriptive bibliographic summary

To complement the qualitative synthesis, a limited descriptive bibliographic summary of the same 75 included studies was prepared. The procedure is not a reproducible network analysis. Counting and normalisation methods, minimum occurrence thresholds, the treatment of author keywords versus Keywords Plus, a cluster-detection algorithm, a citation retrieval date, a thesaurus file, a country-assignment rule, and timeslicing parameters were not retained and are not invented. Citation networks and keyword-evolution maps were not performed. What is reported in Sect. 4.5 is a qualitative reading of outlets, recurrent author names, keyword groupings observed during coding, and broadly described geographic concentration in the included corpus.

3.8.1 Purpose of the descriptive bibliographic summary

The descriptive summary served three limited purposes: to locate publication activity in time within the included set; to record recurring combinations of AI technologies and resilience concepts observed in keywords and abstracts; and to note outlets and author names that appear frequently in the coded corpus. These observations corroborate the thematic map; they are not an independent network-analytic result.

3.8.2 Data source and export processes

The descriptive dataset was the final included set ($n = 75$). Recorded fields were authors, year, source, keywords as printed in the paper, and country or region when the paper reported it. Citation counts, where mentioned, were taken as reported in Google Scholar at the time of coding; the retrieval date of those counts was not logged and is not reconstructed.

3.8.3 Tools and analysis methods

Microsoft Excel was used for manual cleaning, tabulation, and simple frequency counts. No co-occurrence matrix, modularity partition, or layout algorithm is reported as a reproducible result. Keyword groupings, collaboration remarks, and outlet lists in Sect. 4.5 should be read as descriptive summaries of the included corpus, not as outputs of a documented network-analytic workflow.

3.8.4 Data cleaning and standardization

Author names and keywords were standardized by hand to merge obvious formatting variants, including AI, A.I., and Artificial Intelligence, and Machine Learning and ML. This cleaning supports consistent counting in Excel. It is not a documented thesaurus with decision rules for every synonym.

3.8.5 Output of the descriptive bibliographic summary

The descriptive bibliographic summary is used only to corroborate the thematic synthesis. It does not claim an independent quantitative map of the field beyond the 75 included studies.

4 Results

4.1 Descriptive overview of included studies

The evidence base analyzed in this review comprised 75 publications that met the full-text eligibility criteria. The analysis proceeded by first building a grounded descriptive map of the corpus through free and axial coding, and then moving toward higher-order interpretation through thematic development [43]. The descriptive layer served two purposes. First, it established where the literature concentrates in terms of supply chain functions, AI capability types, and resilience outcomes. Second, it provided the empirical foundation for the subsequent thematic synthesis by ensuring that the themes emerged from patterns in the coded corpus rather than from pre-specified assumptions [43].

At the descriptive level, the coding work organized each study around three clusters: Context (the supply chain function or operational domain), Intervention (the AI technology or capability), and Outcome (the resilience dimension or performance target) [43]. This tri-cluster structure allowed the literature to be compared consistently even when study designs were heterogeneous, because every publication could be interpreted through the same 'where used, what used, and what resilience outcome is targeted' logic.

4.1.1 Publication trends

The temporal pattern of publications indicates that AI-SCRES research is a rapidly expanding domain. The corpus exhibits modest output in the earlier years of the review

window and then a sharp acceleration after 2020. Specifically, publication volume increased from fewer than 10 publications per year during 2015–2018 to more than 40 publications per year during 2023–2025, indicating a strong growth trajectory in both scholarly attention and conceptual development. The post-2020 surge aligns with the intensified disruption environment and the corresponding rise in academic and managerial concern with supply continuity, visibility, and adaptive decision-making.

4.1.2 Research methods used (conceptual, simulation, empirical, mixed)

Across the 75-study corpus, the methodological profile is dominated by conceptual and model-driven work that aims to explain mechanisms and propose structures for AI-enabled resilience, often supported by simulation-oriented reasoning rather than large-scale empirical validation. This methodological tendency is visible in how many studies emphasize 'capability mapping' and conceptual structuring, for example, the decomposition of AI into reasoning, prediction, perception, and interaction capabilities and the mapping of these capabilities to resilience outcomes and disruption-stage needs [16].

Within the coded evidence, the more empirically grounded contributions appear most often where implementation processes and adoption challenges are discussed, since organizational constraints and governance limitations are difficult to capture fully in purely technical demonstrations. The descriptive analysis, therefore, indicates a field that is advanced in conceptual articulation but still building toward systematic empirical corroboration, particularly for outcomes beyond short-horizon responsiveness.

4.1.3 Application domains (forecasting, inventory, logistics, and supplier relationship management)

The Context cluster revealed a clear concentration in a small number of supply chain functions. The largest share of studies focuses on demand management, where AI is used to increase forecast accuracy and stabilize planning outcomes in ways that reduce exposure before a disruption occurs [43]. This emphasis reflects the practical reality that forecasting errors amplify vulnerability by driving inventory instability and operational mismatch, and also reflects that forecasting provides measurable performance outcomes that are amenable to AI evaluation. A second major concentration is inventory control, where AI is used to optimize safety stock placement, support dynamic warehousing decisions, and improve buffer allocation under uncertainty.

These studies are frequently connected to robustness and preparedness outcomes because inventory is one of the most direct levers through which organizations absorb shocks. In contrast, Supplier Relationship Management (SRM) appears comparatively underrepresented in high-quality empirical contributions, especially in relation to deep-tier risk and multi-tier supplier vulnerability. The descriptive mapping, therefore, indicates that the literature's functional focus is uneven, with stronger coverage of demand and inventory functions and weaker coverage of upstream supplier-network resilience, where visibility constraints are frequently most severe.

4.1.4 AI techniques distribution

The Intervention cluster produced a structured view of AI technologies by organizing them into four primary capability families: reasoning, prediction, perception, and interaction [16]. This capability-based organization is important because it goes beyond

listing technologies and instead clarifies the decision role each capability plays in resilience. Prediction capability is dominated by Machine Learning (ML) and Deep Learning (DL) approaches applied to demand forecasting, lead-time forecasting, and early warning, forming the core technical foundation of foresight-oriented resilience interventions. Reasoning capability includes automation and optimization-driven decision support, where AI is applied for rapid execution and resource allocation under disruption conditions. Perception capability refers to AI's ability to fuse heterogeneous real-time information streams, including signals derived from IoT and external feeds, to detect weak early indicators and convert fragmented signals into actionable situational awareness. Interaction capability includes conversational AI and generative AI mechanisms that support managerial decision-making by synthesizing complex information and documentation and by accelerating interpretation and learning processes [16].

This descriptive decomposition suggests that the AI–SCRES literature increasingly treats AI not merely as a prediction engine but as a multi-capability architecture that supports sensing, decision orchestration, execution acceleration, and organizational learning.

4.1.5 Resilience dimensions addressed (preparedness/response/recovery/adaptation)

The Outcome cluster mapped studies to resilience attributes with distinct emphases. Robustness codes concentrate on the ability to withstand shocks without immediate failure and are frequently linked to preventive mechanisms and quality control logic. Agility codes emphasize speed of detection, assessment, and coordinated response once a disruption begins, and are strongly associated with automation and predictive alerts because they reduce the latency between recognizing a disruption and executing a response [10].

Adaptability codes capture the capacity to reorganize the supply chain network itself in response to systemic shifts, which moves the discussion beyond short-horizon response toward structural evolution in network configuration and strategy [10]. Taken together, the descriptive evidence shows that AI is positioned across the disruption lifecycle rather than being restricted to one resilience phase. However, the descriptive coding also reveals that adaptation-oriented outcomes tend to require bigger organizational change and thus often appear in the literature as conceptual or framework-based arguments rather than as empirically validated effects.

Overall, the findings in Sect. 4.1 show the distribution of AI–SCRES studies across time, regions, and publication outlets, highlighting the field's rapid growth and concentration in specific domains.

4.2 Structured overview of included studies

The reviewed studies exhibit substantial diversity in terms of methodological approaches, application contexts, and the types of artificial intelligence techniques employed to enhance supply chain resilience. To provide a transparent and structured overview of this body of literature, a comprehensive synthesis of all included studies is presented in a table in the annexes, where each reference is systematically categorized based on its methodological design, AI capabilities, resilience dimensions, and key contributions. However, given the large number of studies included in this review, a selected subset of representative and high-impact studies is presented in the following tables.

These studies are chosen to illustrate the dominant patterns, thematic trends, and critical insights identified through the analysis, while ensuring readability and coherence in the presentation of results. This approach allows the paper to balance comprehensiveness with clarity, directing interested readers to the appendix for the full, detailed mapping of the literature.

4.2.1 Core AI–SCRES studies

See Table 3.

4.2.2 Predictive AI/forecasting/risk detection

See Table 4.

4.2.3 Digital twins/simulation/advanced systems

See Table 5.

4.2.4 Automation/execution (RPA, prescriptive AI)

See Table 6.

4.2.5 Governance, trust, XAI

See Table 7.

4.2.6 Dynamic capabilities theory

See Table 8.

4.3 Thematic synthesis findings (core analytical themes)

After descriptive mapping, the analysis progressed to higher-order thematic development by integrating the descriptive codes into four overarching analytical themes [43]. These themes are shown in Table 9 and organize not only the uses of AI reported in the corpus, but also the synthesis logic through which AI is associated with resilience value, the organizational capabilities proposed as mediating channels, and the governance and maturity foundations proposed as boundary conditions.

4.3.1 Theme 1: AI as a foresight amplifier

The first theme identifies AI's strongest contribution to SCRES as its role as a foresight amplifier, shifting risk management from reactive mitigation to proactive avoidance and readiness [27]. The coded evidence indicates that traditional risk approaches remain constrained by historical reliance and generic assumptions, leaving organizations exposed to disruption patterns that are difficult to anticipate through conventional dashboards. AI is presented as overcoming this limitation by processing weak, heterogeneous signals that are often invisible to human analysts, including unstructured geopolitical information, supplier financial cues, and subtle climate fluctuations [58]. The core mechanism within this theme is the achievement of predictive fidelity, meaning that prediction is not only accurate but decision-relevant in its timeliness, specificity, and operational usefulness [28].

ML and DL approaches are described as particularly valuable in volatile environments because they capture nonlinear relationships embedded deep in supply networks,

Table 3 Core AI-SCRES studies

Study	Method	SC context	AI technique	AI capability	Resilience dimension	Dynamic capability	Key findings	Challenges	Evidence weight
[8]	Conceptual	Risk mitigation	ML, predictive analytics	Prediction	Preparedness	Agility	Real-time analytics improves early detection	Data quality	Low
[10]	Mixed	SC operations	AI-enabled systems	Reasoning	Response	Agility	AI accelerates disruption response	Integration complexity	Medium
[11]	Empirical	Risk management	Deep learning	Prediction	Response	Agility	AI improves risk detection & agility	Model complexity	Low
[12]	Conceptual	SC optimization	AI framework	All	All	All	Integrated AI-resilience framework	Implementation barriers	Medium
[18]	Empirical	SMEs manufacturing	AI analytics	Prediction	Preparedness	Adaptability	AI improves resilience via dynamic capabilities	Data limitations	Limited support
[16]	Conceptual	General SC	AI capability framework	Prediction/ Reasoning/ Perception	All	Agility & Adaptability	AI enables a multi-capability resilience architecture	Lack of empirical validation	Limited support
[45]	Empirical	SC performance	AI-driven innovation	Prediction	All	Innovation	AI enhances resilience & performance	Organizational readiness	Low
[14]	SLR	SC resilience	AI + Big Data	Prediction	All	Agility	AI enhances resilience via analytics	Fragmented evidence	Low

Table 4 Predictive AI, forecasting, and risk detection

Study	Method	SC context	AI technique	AI capability	Resilience dimension	Dynamic capability	Key findings	Challenges	Evidence weight
[13]	Review	Demand forecasting	Big data analytics	Prediction	Preparedness	Agility	AI improves forecast accuracy	Data integration	Low
[26]	Review	Time series	ML models	Prediction	Preparedness	Agility	ML improves forecasting under uncertainty	Model generalization	Low
[27]	Conceptual	Risk management	AI tools	Prediction	Preparedness	Agility	AI manages known/unknown risks	Uncertainty modeling	Low
[28]	Empirical	Risk analytics	AI/analytics	Prediction	Preparedness	Agility	AI improves risk signal detection	Transition barriers	Low
[46]	Empirical	Forecasting	DL + SHAP	Prediction	Preparedness	Agility	Interpretable DL improves forecasting	Complexity	High
[47]	Empirical	Sales forecasting	DNN versus ARIMA	Prediction	Preparedness	Agility	AI outperforms traditional models	Data dependency	Low

Table 5 Digital twins, simulation, and advanced systems

Study	Method	SC context	AI technique	AI capability	Resilience dimension	Dynamic capability	Key findings	Challenges	Evidence weight
[25]	Review	SC management	AI systems	All	All	Adaptability	AI enables integrated resilience	Skills gap	Medium
[48]	Review	SC systems	Digital twins	Perception	Response	Agility	DT enhances visibility & simulation	High cost	Medium
[49]	Empirical	Crisis SC	Data-driven models	Prediction	Response	Agility	Data improves crisis response	Data fragmentation	Low

Table 6 Automation and execution (RPA and prescriptive AI)

Study	Method	SC context	AI technique	AI capability	Resilience dimension	Dynamic capability	Key findings	Challenges	Evidence weight
[50]	Conceptual	Decision-making	Symbolic AI	Reasoning	Response	Agility	Prescriptive AI supports decisions	Complexity	Medium
[30]	Case study	Procurement	RPA	Reasoning	Recovery	Agility	RPA improves execution speed	Implementation cost	Low

improving early warning capacity and extending the managerial planning window. This temporal extension is strategically important because it allows organizations to treat a disruption as a scheduled event rather than an emergent surprise, creating the option to pre-position buffers, adjust sourcing, or reroute flows in advance [28].

The theme also highlights that foresight does not remain abstract. Digital twins are described as a mechanism that converts AI prediction into actionable scenario planning by allowing organizations to simulate cascading disruption effects and evaluate mitigation strategies before a disruption fully materializes, thereby reducing recovery time and strengthening response agility [11].

Nonetheless, there is disagreement among the analyzed studies over whether AI consistently enhances foresight in all disruptive scenarios. According to a number of studies, the availability of high-quality historical data is crucial for predicting performance, which makes AI significantly less dependable amid unprecedented disruptions when historical patterns are no longer valid. Further, discussions of pandemic-scale disruptions and geopolitical shocks, where quickly shifting circumstances diminished the efficacy of models educated on past observations, made this restriction very clear. Thus, when disruptions occur outside of previously recognized operational parameters, AI should be seen as supplementing rather than replacing managerial discretion.

4.3.2 Theme 2: dynamic capabilities as mediators

The second theme indicates that the literature frequently associates AI with resilience outcomes through a potential role for dynamic capabilities, with agility and adaptability emerging as the two capability paths through which AI is converted into realized resilience [10, 16].

The literature argues that AI should be understood as a digital enabler of a firm's ability to perceive changes, seize opportunities through fast response, and transform its resource base and network structure, rather than as a self-contained competency [10]. The synthesis distinguishes two levels of AI-enabled dynamic capability. The first is operative dynamic capability (agility), where AI's reasoning and automation capabilities accelerate response speed within the current supply chain structure [10]. This includes automated optimization models that reroute shipments, modify inventory positioning, or trigger supplier switching within predefined policy boundaries. The deep-dive evidence further emphasizes that speed is decisive after disruption detection, and that automated prescriptive analytics can both recommend and initiate early execution steps, reducing the latency between sensing and seizing [10, 50].

Table 7 Governance, trust, and XAI

Author (year)	Method	SC context	AI technique	AI capability	Resilience dimension	Dynamic capability	Key findings	Challenges	Evidence weight
[22]	Empirical	AI adoption	AI systems	Interaction	All	Adoption	Trust determines AI usage	Lack of transparency	High
[51]	Review	General	XAI	Interaction	All	Adoption	XAI improves transparency	Model complexity	High
[24]	Conceptual	Governance	AI governance	Interaction	All	Adoption	Governance frameworks essential	Policy gaps	High
[52]	Conceptual	AI ethics	AI models	Interaction	All	Adoption	Transparency needed for trust	Ethical risks	High
[53]	Review	ML models	Explainability	Interaction	All	Adoption	Black-box problem limits adoption	Interpretability gap	High
[54]	Empirical	SC risk	XAI	Interaction	Response	Agility	XAI improves trust in SC decisions	Implementation complexity	High
[55]	Review	General	XAI	Interaction	All	Adoption	XAI critical for decision-making	Technical difficulty	High
[56]	Review	General	XAI	Interaction	All	Adoption	Trustworthy AI requires explainability	Ethical concerns	High

The second level is strategic dynamic capability (adaptability and innovation), which the reviewed literature links conceptually to AI's perception and interaction capabilities, such as digital twin simulation and generative synthesis of complex strategic information [25]. Adaptability is conceptualized as the organizational capacity to restructure the network in response to persistent systemic change, such as moving from single sourcing to multi-sourcing or shifting production footprints [59]. AI is described as enabling this

Table 8 Dynamic capabilities theory

Author (year)	Method	SC context	AI technique	AI capability	Resilience dimension	Dynamic capability	Key findings	Challenges	Evidence weight
[21]	Empirical	Firm performance	AI	All	All	Innovation	AI improves adaptive response	Organizational complexity	Low
[36]	Conceptual	Competitive advantage	AI	All	All	Adaptability	AI aligns with RBV	Limited empirical support	Low
[57]	Empirical	SC resilience	AI systems	All	All	Agility & Adaptability	DC mediates the AI–SCRES link	Measurement issues	Low

Table 9 Thematic synthesis findings

Theme	Core concept	Codes (representative examples)	Proposed synthesis link
I Foresight Amplification	Predictive Fidelity	ML-driven forecasting, Real-time data fusion, Early warning systems, Lead-time variability reduction, Risk signal detection.	Prediction\Uncertainty Reduction\Agility
II Dynamic Capabilities theory	Operative versus Strategic DC	Response speed, Network reconfiguration, Systemic learning loops, Post-disruption analysis, non-imitable advantage.	AI\DCF\SCRES
III Governance & Trust Deficit	Managerial Acceptance	Black box problem, Interpretability requirement, Algorithmic bias, Managerial override, Auditability, XAI mechanisms.	XAI\Trust\Adoption
IV Paradoxical Boundary	Digital Maturity, Data quality	Data silos, Skills gap, High implementation cost, Data scarcity, Cultural resistance, and Infrastructure fragility.	Digital readiness conceptualised as a boundary condition on success

shift by translating unstructured information into strategic insight and by accelerating evaluation of long-term trade-offs of structural change [25].

The thematic conclusion is therefore that AI supports a transition from short-horizon agility benefits to long-horizon adaptation and innovation that is difficult to replicate as a strategic advantage [59]. However, the evidence examined shows significant diversity between organizational contexts and sectors. Meantime, compared to small and medium-sized businesses, whose AI implementation is constrained by fragmented information systems and insufficient analytical capabilities, large multinational corporations with established digital infrastructures typically report greater improvements in agility and adaptable capability. In addition, a number of implementation studies indicate that organizational capabilities, rather than AI technology itself, remain the main factor influencing resilience improvement. This suggests that AI is not enough to produce dynamic capabilities on its own without additional managerial and organizational investments.

4.3.3 Theme 3: governance and trust deficit

The third theme identifies a central limiter: a governance and trust deficit that can reduce AI's resilience benefit to zero if managers do not accept or use the recommendations in high-pressure disruption contexts [52]. The literature highlights a recurring opacity-performance trade-off, in which highly powerful models (particularly DLs) can be difficult to interpret, creating a 'black box' that impedes due diligence and root-cause interrogation of decisions, which is especially problematic when disruption decisions carry high financial and reputational stakes [52, 53].

XAI is synthesized as a potential organizational mechanism through which computational complexity may be made more compatible with managerial accountability. XAI approaches provide both local explanations (why a particular supplier or action was selected) and global explanations (what features the model generally prioritizes), thereby supporting managerial trust and enabling adoption under pressure [54]. The deep-dive evidence emphasizes that trust failure leads to algorithmic override, especially when recommendations are counterintuitive, and argues that XAI must translate opaque logic into decision-relevant forms such as interpretable dashboards or structured technical reports [55, 60].

Beyond interpretability, the theme emphasizes governance maturity as essential for ethical and accountability protection. High-stakes resilience decisions, such as prioritizing limited supply, have serious ethical implications, and inadequate governance exposes organizations to systemic risk, including algorithmic bias and unfair allocation outcomes [54]. The theme, therefore, suggests that investment in XAI and governance maturity should be considered alongside investment in predictive performance, because the literature indicates that trust and institutional legitimacy may shape AI adoption [56].

4.3.4 Theme 4: paradoxical boundary

The fourth theme frames AI success as contingent on boundary conditions related to data availability and digital maturity. It is described as paradoxical because the very situations where AI would be most valuable, severe disruptions, are often the situations where training data are rare, fragmented, or inconsistent.

The literature describes a cold-start problem for disruption training because severe disruptions are, by nature, infrequent, which reduces forecast fidelity precisely when it matters most [61]. A second part of the paradox is organizational fragmentation. Resilience-critical data, including supplier vulnerabilities, internal capacity constraints, and operational redundancies, are often locked in antiquated systems and dispersed across functional silos, constraining AI feasibility even when algorithms exist [25].

The deep-dive evidence suggests that digital maturity conditions the extent to which organizations can overcome this constraint. Digitally mature firms that have invested in cloud infrastructure, integrated data lakes, and uniform data quality can progress more rapidly to model training and operationalization, whereas low-maturity firms often expend significant resources on cleansing and integration and may fail to reach a viable scale for reliable resilience modeling [25, 37].

The theme also stresses that maturity is not purely technical. Cultural resistance, lack of data literacy among senior managers, and shortages of specialized capabilities represent major barriers, leading to the conclusion that AI tends to accelerate pre-existing organizational strengths rather than compensate for fragmentation [18].

Across the reviewed studies, empirical validation of AI-enabled resilience remains limited. Most published work relies on simulation, synthetic data, or controlled experiments, especially in forecasting, anomaly detection, inventory optimization, and network reconfiguration. These studies demonstrate algorithmic potential but do not fully reflect real operational complexity. Implementation evidence in the reviewed corpus is limited and is primarily reported through individual empirical or case-based studies rather than sector-wide evaluations. These studies mainly concern applications such as predictive analytics, anomaly detection, prescriptive optimization, and automation for disruption response, rerouting, inventory rebalancing, and recovery-related activities. The study-level contexts and evidence characteristics are documented in Appendix Table 14. The reported implementation examples should therefore be interpreted as illustrative study-level evidence rather than as evidence of sector-wide prevalence or statistically tested sector effects. Measurable resilience outcomes include forecast accuracy, anomaly detection precision, lead-time reduction, service-level recovery, and disruption response time.

Measurable resilience outcomes include forecast accuracy, anomaly detection precision, lead-time reduction, service-level recovery, and disruption response time. The strongest evidence lies in predictive analytics and prescriptive optimization, while empirical validation of digital twins, GenAI, hybrid AI, and cross-tier visibility systems remains scarce due to the rarity of disruptions, confidentiality constraints, and difficulty in isolating AI effects from organizational capabilities.

4.4 Integrated framework/model derived from synthesis

4.4.1 Framework constructs and relationships

The synthesis was consolidated into an integrated conceptual model that explains how AI-related capabilities may contribute to supply chain resilience through organizational capability pathways and under specific enabling or constraining conditions. Specifically, agility and adaptability are proposed as conceptual mediating processes through which AI-related resources are translated into resilience outcomes. Agility represents the conversion of AI-generated insights into rapid operational responses within the existing supply chain configuration, whereas adaptability represents the use of AI-supported learning and analysis to facilitate longer-term structural reconfiguration. Governance maturity and digital readiness are conceptualized as distinct boundary conditions that enable or constrain the operation of these capability pathways. This framework is derived from the thematic synthesis and represents a conceptual proposition rather than an empirically estimated mediation or moderation model; therefore, no mediation or moderation effects are statistically tested in this study.

The framework distinguishes between operative AI (execution) that primarily supports agility and strategic AI (foresight and learning) that primarily supports adaptability and structural reconfiguration [18]. The model proposes governance and trust as boundary conditions rather than as secondary implementation issues. The proposed linkage between dynamic capabilities and resilience outcomes is described as fragile when explainability is insufficient for managerial interrogation or when governance maturity lacks auditability and institutional control [18].

The model also incorporates boundary conditions of digital maturity and data quality as feasibility requirements for the entire pathway, because low maturity can undermine

the process before AI generates its first reliable prediction [16]. The integrated AI–SCRES framework can also be interpreted as a DSS architecture: (i) data and sensing inputs, (ii) predictive and prescriptive analytics engines, (iii) governance and explainability mechanisms, and (iv) decision execution and learning loops. This interpretation aligns with supply chain risk management research that positions DSS as the operational vehicle connecting analytics to action, and with recent DSS literature emphasizing that explainability features are increasingly required when AI is used for high-impact operational decision support [32].

4.4.2 Mapping AI capabilities to resilience stages

When mapped onto disruption stages, the framework positions foresight-oriented AI as dominant in preparedness. Predictive fidelity improves early warning and extends planning windows, enabling pre-emptive reallocation and stress testing before disruption occurs [28].

During response, execution-oriented AI supports agility by reducing sense–seize latency through automation and prescriptive decisioning, including rapid operational reconfiguration such as rerouting and automated contingency execution [10, 50]. During recovery and development, learning-oriented AI supports adaptation by enabling deeper diagnosis, institutional learning loops, and simulation-driven prototyping of alternative network structures, thereby supporting strategic reconfiguration capacity [16, 45].

4.4.3 Practical interpretation of the framework (how to use it)

The integrated model can be interpreted as a structured decision guide for aligning AI investments with resilience objectives. Organizations that prioritize short-horizon disruption response can focus on execution and reasoning capabilities that drive agility, provided governance and trust foundations support operational adoption. Organizations that face persistent systemic uncertainty can focus on foresight and learning capabilities that drive adaptability, particularly through simulation and learning loops that support structural network redesign. Across both pathways, the model implies that AI investment without attention to digital maturity and governance conditions is structurally fragile, because low data quality, siloed infrastructure, and weak trust processes can prevent adoption and undermine resilience rather than strengthen it [37, 54].

4.4.4 Rationale for the proposed capability paths and constraints

Agility and adaptability are proposed as capability paths, not as synonyms for resilience, and not as additional AI techniques. The coded corpus repeatedly describes AI as an input that remains inert unless organizations convert signals into coordinated action. Agility is that conversion inside the current network. It is an operative dynamic capability. It shortens the interval between sensing a disruption and seizing a feasible response such as rerouting, supplier switching, or inventory rebalancing [10, 21]. Adaptability is a different conversion. It uses AI-supported diagnosis and simulation to change the structure that produced the vulnerability, including sourcing footprints, buffer policies, and planning logics [16, 21]. The two paths are kept distinct because speed within an unchanged architecture does not accomplish the same work as redesign of that architecture.

In the proposed architecture, agility and adaptability are specified as conceptual mediating processes rather than as empirically estimated mediators. They describe the organizational conversion through which AI-related resources are associated with resilience outcomes: agility operates within the existing supply chain configuration, whereas adaptability operates through structural reconfiguration over a longer horizon. Governance maturity and digital readiness are specified as boundary conditions that enable or constrain whether those conversion processes can operate. They are not specified as moderators in a statistical sense, because the synthesis does not estimate interaction effects. Digital readiness is treated as a feasibility condition for data, infrastructure, and skills; governance maturity is treated as an institutional condition for auditability, accountability, override protocols, and contestable explanations. Both are necessary conditions in the conceptual model, not additional mediating capabilities. This specification is a synthesis-derived proposition and is not presented as a validated causal pathway.

Governance maturity and digital readiness are conceptualized as constraints rather than as further paths because they gate whether conversion can occur. Digital readiness is the feasibility constraint. Without integrated data, interoperable systems, and domain-literate skills, models cannot be trained or fed at disruption speed, so the agility path never starts [19, 20, 25]. Governance maturity is the adoption constraint. Without audit trails, role clarity, override rules, and contestable explanations, even accurate recommendations may be unused or indefensible when managers remain accountable for shutting a plant or rationing scarce supply [22, 56, 60]. The two constraints are independently necessary. Digital readiness without governance yields technically capable systems that remain unused. Governance without digital readiness yields accountable procedures around models that cannot see the network. Tables 10 and 11 should be read as a synthesis-derived schematic of this conversion architecture. They are not a fitted structural model, and they do not report mediation or moderation coefficients.

Table 10 Synthesis-derived framework constructs

Component	Theme	Proposed synthesis mechanism	Function in model
Input (X)	Foresight Amplification	Prediction of vulnerability reduces uncertainty.	Exogenous Variable
Proposed conceptual mediator 1 (Agility)	Operative DC (Agility)	Automation accelerates operational response speed.	Proposed conceptual mediating process linking AI-enabled operational capabilities to SCRES
Proposed conceptual mediator 2 (Adaptability)	Strategic DC (Adaptability)	Learning/Simulation enables network reconfiguration.	Proposed conceptual mediating process linking AI-enabled learning and reconfiguration capabilities to SCRES
Boundary condition (governance)	Governance & Trust Deficit	XAI is proposed to reduce black-box risk and to support managerial interrogation.	Conceptualized as conditioning the M1/M2-SCRES link
Boundary Condition	Paradoxical Boundary	Digital Maturity determines the initial feasibility and scale of AI implementation.	Precondition for the entire Model
Output (Y)	SCRES Performance	Proposed resilience outcomes: Potential improvements in recovery time, operational continuity, and longer-term structural resilience, subject to empirical validation.	Dependent Variable

Table 11 Governance maturity versus digital readiness as proposed boundary conditions

Construct	Definition used in this synthesis	Primary failure mode if weak	Role in the proposed framework
Governance maturity	Institutional feasibility of using AI under accountability pressure: audit trails, role clarity, override and escalation protocols, ethical criteria for allocation under scarcity, and explanations sufficient for contestable decisions [22–24]	Technically capable models remain unused or indefensible during disruption	Conceptualised as a boundary condition on the adoption of AI-supported decisions
Digital readiness	Technical and human feasibility of deploying AI: integrated data architecture, interoperable systems, timely feeds, and skills spanning analytics and supply chain domain literacy [19, 20]	Models cannot be trained or fed reliable inputs at disruption speed	Conceptualised as a feasibility boundary condition on the entire pathway

4.5 Descriptive bibliographic observations

A limited descriptive bibliographic reading of the 75 included studies is used to corroborate the thematic synthesis. The observations below concern outlets, recurrent names, keyword groupings, and broadly described geographic concentration. They are not a parameterized co-occurrence, co-citation, or collaboration network. Citation networks and keyword-evolution maps were not performed.

4.5.1 Leading journals/sources and most influential publications

The most influential journals in the corpus were Computers & Industrial Engineering, International Journal of Production Research, Supply Chain Management: An International Journal, and Transportation Research Part E: Logistics and Transportation Review, reflecting the interdisciplinary intersection of operations research, production systems, and supply chain management in the AI–SCRES domain.

4.5.2 Recurrent authors and intellectual structure as observed in the included set

Recurrent author names in the included set and in the reference lists of those studies include Ivanov, Dolgui, Modgil, Singh, and Wong. These names are noted because they appear repeatedly in the coded corpus, not because a co-citation matrix, clustering algorithm, or citation window was estimated. The observation is consistent with a gradual overlap between resilience theory and digital transformation research, and with the later incorporation of machine learning, predictive analytics, and digital twins into resilience decision discussions. That reading remains qualitative.

4.5.3 Keyword groupings observed in the included corpus

Four keyword groupings were observed during coding of the included corpus: an AI technology grouping (machine learning, deep learning, predictive analytics, digital twins); a resilience grouping (agility, robustness, recovery, adaptive); a disruption grouping (disruption management, supply risk, uncertainty, vulnerability); and an Industry 4.0 grouping (cyber-physical systems, IoT, automation, smart logistics). These groupings are descriptive consolidations of recurrent terms. They are not the output of a documented co-occurrence threshold, normalization, or cluster algorithm.

These descriptive keyword groupings align with the thematic synthesis by reinforcing the centrality of predictive and digital twin capabilities, the prominence of agility and adaptability as proposed mediating constructs, and the increasing attention to interpretability and governance-related terms.

4.5.4 Geographic and institutional patterns

The geographic distribution of publications shows concentration in Europe (including the UK, Germany, and the Netherlands), Asia (notably China and India), and North America (USA and Canada). This distribution suggests that AI–SCRES research is driven largely by research-intensive institutions in regions with strong industrial supply chain bases and mature technology research ecosystems.

4.5.5 How the descriptive bibliographic observations corroborate the thematic findings

The descriptive bibliographic observations corroborate the thematic synthesis in four limited ways. The recurrence of predictive analytics and digital twins is consistent with the foresight-amplifier theme. The joint appearance of agility and adaptability is consistent with the proposed mediating role of dynamic capabilities. The appearance of terms such as bias, transparency, interpretability, and XAI is consistent with the governance and trust theme. The appearance of terms such as big data, data quality, and integration is consistent with digital readiness as a boundary condition. These correspondences are interpretive.

The coded literature increasingly discusses explainable, reliable, and human-centered AI, as well as digital twins and governance. That shift is a qualitative reading of recent papers in the included set, not a thematic evolution or co-citation forecast.

5 Discussion

5.1 What the findings mean for theory

The literature is more consistent with a mediated and conditional account. AI is associated with resilience through two capability paths, agility and adaptability, and those paths operate only when two constraints are present: governance maturity and digital readiness [18]. Agility converts AI signals into action inside the current architecture. Adaptability converts AI-supported learning into structural change. Digital readiness constrains whether models can be fed. Governance maturity constrains whether recommendations can be used. That account is a synthesis proposition, not an estimated path model. Theoretical definitions of the two constraints remain those stated in Sect. 2.5.

From the perspective of dynamic capabilities, the thematic results refine the Sense-Seize-Transform logic by specifying how these components operate in resilience contexts when AI is present. The sensing component is best interpreted as foresight amplification, where the literature associates AI with improved predictive fidelity by integrating diverse signals and reducing perceived environmental uncertainty (PEU) [63, 64]. Traditional approaches are described as generating excessive false alarms or missing real threats, while AI-enabled detection and sensor fusion are argued to increase true positive detection and reduce noise [65].

The seizing component is conceptually split into two forms because the literature reports short-horizon speed and long-horizon redesign as different organizational tasks. Operative seizing corresponds to agility within the existing supply chain architecture, enabled by execution and reasoning capabilities such as automation and rapid reconfiguration routines. Strategic seizing corresponds to adaptability, where AI enables structural change through learning and simulation-based exploration of alternative network designs [21]. Treating the two as one capability would hide why firms can become faster at rerouting without becoming less fragile.

This distinction is theoretically important because it clarifies why much of the literature reports strong short-horizon gains (agility) while long-horizon resilience (adaptability) remains difficult and more dependent on organizational learning. In this context, the synthesis emphasizes double-loop learning as a key mechanism of strategic resilience: AI supports not only the correction of immediate failures but also questioning and redesign of the assumptions and structures that created vulnerability in the first place [21].

Within resilience theory, these findings support an evolutionary view of SCRES, where the highest form of resilience is not merely recovery but the ability to become structurally less fragile after disruption. This is consistent with the argument that AI's strategic value extends beyond 'weathering the current storm' to enabling continuous learning and network hardening over time [16].

From the Resource-Based View (RBV), the results sharpen what constitutes the scarce and defensible resource in AI-enabled resilience. The evidence indicates that the VRIN-like asset is not the AI model itself (which may be open-source or widely replicable) but digital maturity, conceptualized as integrated data infrastructure, specialized human capital (including data literacy), and the organizational slack required to institutionalize governance and trust mechanisms [19, 20]. The RBV implication is that sustained resilience advantage arises from the organizational capability to deploy, govern, and learn from AI in high-stakes environments, rather than from access to algorithms. This also provides a coherent explanation for contradictory findings in the literature: organizations with similar AI tools can experience very different resilience outcomes if their maturity conditions differ [19].

Finally, the synthesis supports an integrated theoretical viewpoint that combines technology, behaviour, and institutions. The proposed framework posits that managerial trust is a potential mediating channel from AI capability to dynamic capabilities, and that AI governance maturity is conceptualised as a boundary condition on whether technical performance translates into adoption and resilience outcomes [66]. This proposition addresses technological determinism by indicating that high-performing models can still fail to produce realized resilience if the human-institutional layer is weak. The claim is bounded by a heterogeneous, largely non-causal evidence base.

Three evidential statuses are distinguished throughout the synthesis. Thematic associations are recurring patterns identified through coding across the 75 included studies and are reported as associations, not as effect estimates. Conceptual propositions are synthesis-derived statements that integrate those patterns into the conversion architecture; they specify proposed relationships among AI capability families, agility, adaptability, governance maturity, digital readiness, and resilience outcomes. Empirical validation refers to study-level findings reported in the included corpus, including forecast accuracy, anomaly detection precision, lead-time reduction, service-level recovery, and disruption response time. Unless a statement is explicitly identified as an empirical finding from an included study, the claims in this paper are thematic associations or conceptual propositions. No relationship in the framework is presented as an empirically validated mediation or moderation effect.

5.2 What the findings mean for practice

The practical pattern across the literature is that AI delivers the clearest benefits where resilience requires (1) fast conversion of signals into actionable forecasts and (2) rapid

evaluation of response options under constraints. In preparedness contexts, AI is repeatedly framed as improving resilience by reducing PEU and increasing predictive fidelity through integration of heterogeneous structured and unstructured signals [63, 64].

In practical terms, this shifts disruption management from late reaction to earlier preparation by enabling more confident pre-positioning decisions and earlier contingency activation. In response contexts, the literature emphasizes that organizations gain the most when AI supports execution acceleration and reduces the latency between sensing and action. This includes rapid operational reconfiguration and automation-supported decision execution, particularly when disruptions compress decision windows [21].

The evidence also shows consistent failure modes. The most common failure is not that AI does not work, but that it is not adopted or cannot be operationalized at disruption speed. Technical complexity without interpretability can lead to non-use in a crisis because decision-makers cannot defend the recommendation. Data fragmentation and legacy silos create situations where models cannot be trained reliably or cannot receive timely inputs when disruptions unfold [25, 37]. Organizations often underestimate the human-capital transformation required, so that without AI literacy and cross-functional collaboration AI remains an isolated technical initiative rather than a strategic resilience system [67].

From a managerial standpoint, the results imply that resilient AI deployment should be treated as a socio-technical program: the highest returns are discussed where predictive and execution capabilities are aligned with governance, skills, and integrated data foundations, rather than where algorithm sophistication is pursued in isolation [18]. Managers should treat simulation-based results cautiously, as they often assume data quality and integration levels not present in many organizations. Illustrative implementation examples in the corpus concentrate in digitally mature settings (see Appendix Table 14); firms with fragmented systems may need foundational investments before expecting meaningful resilience gains.

Measurable outcomes such as forecast accuracy, detection precision, and recovery speed provide realistic benchmarks for early evaluation of AI initiatives. Organizations should prioritize AI applications where empirical evidence is strongest, mainly predictive analytics and prescriptive optimization. Because disruptions are rare and heterogeneous, firms should capture disruption data and evaluate AI-supported decisions over time, which can help build the empirical evidence base that the field currently lacks.

5.3 Human–AI decision-making in disruptions

The synthesis identifies a governance and trust deficit as a central bottleneck for realized, as opposed to potential, AI-enabled resilience. In high-stakes disruption settings, managers remain accountable for shutting down production, switching suppliers, or prioritizing scarce supply. When a system recommends a counterintuitive action and cannot produce a contestable explanation, decision-makers may revert to familiar controls [60]. XAI is therefore discussed as a structural remedy that translates model logic into decision-relevant forms [51, 55, 60, 62]. The definitions of trust, governance maturity, and DSS logging remain those in Sect. 2.5 and are not restated at length in Sect. 6.

5.4 Digital maturity as a precondition

AI-associated resilience effects in the corpus are strongly filtered by digital readiness, as defined in Sect. 2.5. The literature frames a paradox: organizations that most urgently need AI-enabled resilience are often those with the most fragmented systems [25, 37]. Severe disruptions are rare, which creates a cold-start problem for training [37], and resilience-critical data are often locked in legacy systems [25]. From a resource-based view, digital readiness, not the algorithm, is the scarce complementary resource that helps explain divergent outcomes among firms using similar tools [19, 20]. Table 11 contrasts this construct with governance maturity so that the two boundary conditions are not collapsed into a single readiness index.

5.5 Ethical and sustainability considerations

Ethical and sustainability issues emerge in the literature as practical constraints because resilience decisions often involve prioritization under scarcity. The evidence highlights that AI can amplify existing biases embedded in historical data. If previous decisions favored certain regions, suppliers, or allocation patterns, AI may reproduce and intensify the same patterns during supplier selection or resource distribution, which can undermine resilience by reducing diversity and increasing systemic vulnerability [14]. This is particularly concerning for SCRES decisions that involve high-stakes trade-offs, such as deciding which customers receive limited supply during shortages, because the ethical implications can translate into legal and reputational risk [54].

Data governance is tightly linked to ethics because AI-enabled resilience requires real-time data exchange across actors and tiers, which increases exposure to cybersecurity risks and the possibility of data manipulation [68]. In addition, model opacity can exacerbate ethical risk because when decisions are not explainable, accountability is weakened and harmful allocation effects become harder to detect and correct [46].

Sustainability constraints appear most explicitly through the energy requirements of large-scale AI systems, particularly deep learning. Training and running such systems can require substantial energy, and this impact is often underemphasized in organizational carbon accounting and reporting. If not measured and managed, AI adoption may conflict with corporate sustainability goals and ESG commitments, which introduces a strategic tension between resilience-building and environmental objectives [69]. The implication is not that AI should be avoided, but that resilience-oriented AI programs should incorporate governance frameworks that treat ethical and environmental considerations as design constraints rather than as afterthoughts [54, 69].

5.6 Critical comparison with prior reviews and theoretical positioning

Published AI-SCRES reviews leave a conversion problem unaddressed. Zamani et al. [14] organize the field into thematic clusters and call for integration across sensing, decision-making, transparency, and learning, but they do not specify agility and adaptability as two capability paths or treat governance maturity as a constraint distinct from digital infrastructure. Smyth et al. [15] locate prescriptive analytics value in structured decision support at the point of action. Riad et al. [12] treat implementation readiness as a success factor without separating institutional governance from technical digital

readiness. Modgil et al. [16] map AI capabilities in a Covid-19 learning setting and do not offer a multi-database structured reading of the subsequent literature. Maharjan and Kato [3] review resilient network design without an AI-capability, XAI, and governance synthesis. The unique increment of this structured narrative synthesis is therefore architectural. It keeps AI families mapped onto disruption stages, specifies two conversion paths, and treats two independently necessary constraints as the conditions under which those paths can operate. The resulting question is not whether AI is associated with resilience in general. It is under what organizational conditions AI is reported to translate into realized resilience. That is a more actionable question. It is not, on the present evidence, an empirically estimated answer.

Smyth et al. [15] report that prescriptive analytics creates resilience value only when embedded in structured decision support that enables supply chain actors to use recommendations at the point of action. The present synthesis is consistent with that reading and extends it. The same adoption barrier is discussed for predictive and learning-oriented AI, not only for prescriptive systems. XAI is proposed as the mechanism that can bridge analytical output and operational action by providing interpretable rationales under time pressure, embedded within a broader governance architecture. That mechanism is a synthesis proposition, not an estimated mediation effect.

Compared with Riad et al. [12], whose conceptual framework treats implementation readiness and organizational fit as key success factors, the present synthesis theorizes digital readiness not as a static checkpoint but as a path-dependent organizational capability shaped by historical investment in data infrastructure and human capital, and it keeps governance maturity as a separate institutional constraint. The implication is that organizations cannot simply achieve readiness at a point in time before deploying AI, but must develop both constraints alongside the AI system itself. This co-evolutionary reading is offered as a structuring contribution and as a precedent that future empirical work can test, not as a completed multi-theoretic estimation.

6 Implications

6.1 Managerial implications

Where AI remains opaque, the black-box problem undermines perceived utility and increases the probability of algorithmic override, which can collapse realized resilience impact [22, 51].

A practical implication is therefore to institutionalize trust through layered explainability and operationalized formal governance protocols. Governance maturity can be specified, at minimum, as named model ownership, a logged override protocol, an audit trail of recommendations and outcomes, and pre-agreed ethical criteria for allocation under scarcity. XAI can be specified as the joint availability of a local rationale for the case at hand and a global account of features the model generally prioritizes, delivered inside the DSS at decision speed. Digital readiness can be specified as integrated master data, timely feeds from planning and logistics systems, and managerial data literacy sufficient to interrogate outputs. These are design requirements derived from the synthesis, not validated maturity scales.

Governance mechanisms must accompany explainability. The recommendations emerging from the synthesis emphasize auditable accountability protocols, including a formal AI audit trail that records when managers override recommendations, why overrides occur, and what outcomes follow. This transforms overrides into learning events and protects the organization against institutional fragility by ensuring that accountability is assigned to specific model owners and governance bodies rather than being displaced onto an opaque system [56].

A second managerial implication concerns investment sequencing. The evidence repeatedly indicates that organizations should prioritize data integration and quality before investing in more sophisticated models. The synthesis frames this as a feasibility constraint: a simpler model operating on clean, integrated data can outperform complex deep learning systems trained on fragmented, inconsistent data streams, especially when decisions must be executed in real time. This sequencing is critical because resilience systems are evaluated during disruptions, which is when poor data quality becomes most damaging.

A third managerial implication is the central role of human capital, specifically data literacy, within supply chain leadership and operational teams. The synthesis argues that skills gaps are not primarily a scarcity of data scientists, but rather a shortage of managers who can interpret model outputs, assess uncertainty, and understand XAI explanations sufficiently to act confidently under disruption. A capability roadmap, therefore, requires structured multidisciplinary training programs that link supply chain domain expertise with analytics interpretation skills.

Finally, for organizations pursuing long-horizon resilience, the implications extend beyond operational agility and into strategic adaptability. The synthesis identifies digital twin and simulation investments as particularly relevant for organizations that face persistent systemic uncertainty and need to evaluate structural trade-offs (for example, regionalization versus global networks or multi-sourcing strategies). Digital twin environments support stress testing and scenario prototyping that can shift resilience from reactive firefighting toward proactive, data-driven network redesign.

6.2 Policy and ecosystem implications

The review's findings suggest that many resilience failures are ecosystem-level rather than firm-level, particularly where upstream visibility is limited and disruption-relevant data are sparse. This implies a policy and industry-consortium role in shaping the institutional environment in which AI-enabled resilience is deployed. One core implication is the need for cross-industry standards that reduce adoption barriers, especially for small and medium-sized enterprises that cannot develop bespoke governance and explainability solutions.

A priority recommendation is the development of standardized documentation and reporting requirements for AI systems used in supply chain risk and resilience decisions, with a focus on algorithmic transparency and explainability. In institutional terms, standardized XAI documentation supports legitimacy and compliance-compatible use of AI by creating shared expectations about what must be disclosed, how models should be audited, and how bias and limitations should be reported [23]. The synthesis also

indicates that without such governance structures, organizations tend to revert to slower and more familiar decision routines under pressure, a pattern aligned with institutional inertia [24].

A second ecosystem implication is the need to address the 'data scarcity paradox,' where disruptions are precisely the events that require AI most, but also the events for which training data are rare and inconsistent. The evidence highlights that overcoming disruption-data scarcity is difficult for single firms acting alone and requires collaboration mechanisms that enable secure, anonymized sharing of non-competitive disruption data. This would allow organizations to pool rare-event datasets (for example, port closures, geopolitical shocks, and deep-tier supplier failures) and thereby improve model robustness across the ecosystem.

Finally, policy has a direct role in strengthening the governance foundations needed for responsible adoption. High-stakes resilience decisions involve allocation under scarcity, and weak governance creates legal and reputational exposure. The synthesis indicates that governance frameworks should therefore define accountability structures and human-in-the-loop requirements explicitly for high-impact decisions, reducing ambiguity about responsibility when automated recommendations contribute to major loss events [54, 56].

6.3 Research implications

The synthesis indicates several research implications that follow from the current evidence distribution and its limitations. The AI-SCRES field remains comparatively weak in cross-industry empirical validation, particularly for evaluating the return on investment and effectiveness of different AI approaches across multiple disruption types. Much of the literature remains conceptual or simulation-oriented, so that many claims reflect technical feasibility or theoretical promise rather than measured resilience outcomes in operating environments.

Future research should move beyond asking whether AI is associated with resilience and focus instead on when and why that association is reported. The conceptual model implies that governance quality and managerial trust are not peripheral variables but central mechanisms shaping adoption under pressure. The literature therefore supports empirical work that measures explainability quality, operational adoption, and trust dynamics, and that tests how these variables relate to resilience outcomes through organizational decision-making behaviour [56].

Digital readiness should be operationalized explicitly as a distinct contingency. The evidence frames AI success as contingent on integrated data infrastructure, data literacy, and the organizational slack needed to build governance and trust structures [19, 20]. Future models should incorporate digital readiness as a control or proposed moderating variable when evaluating AI-associated resilience effects, because ignoring it can lead to inconsistent findings.

The literature emphasizes that resilience-relevant AI research must account for disruption rarity and heterogeneity. Severe disruptions produce a cold-start training problem and create generalization challenges for predictive systems, which suggests that

methodological innovation is needed in learning from limited rare-event data and in validating systems under extreme, non-linear conditions [25, 37].

Ethical and governance issues should be treated as primary research objects rather than as secondary limitations. Resilience decisions can involve ethically sensitive allocation choices under scarcity, and governance weaknesses create institutional risk. Research that evaluates concrete governance mechanisms, auditability designs, and the effectiveness of human-in-the-loop structures in reducing bias and improving adoption would materially strengthen the field's ability to translate AI potential into reliable operational resilience [23, 54].

6.4 Operationalising governance, XAI, and digital readiness

Section 6.1 specified governance maturity, XAI, and digital readiness as design requirements derived from the synthesis rather than as validated maturity scales. Table 12 translates those requirements into a minimum operational specification and into three staged states that organisations can use as a sequencing guide. The stages are synthesis-derived. They are not an estimated index, a scored checklist, or a claim that any included study administered this instrument.

These specifications can be used as a sequencing guide: data integration and named accountability precede more sophisticated models; local explanations in the DSS precede reliance during a live disruption; override logs convert exceptions into learning events. None of the stages is a validated instrument.

7 Conclusion

7.1 Summary of main findings

This structured narrative synthesis examined 75 studies that met the inclusion criteria and were published from 2015 to 2025, with the search conducted through January 2026, to examine how AI is discussed as contributing to supply chain resilience. Thematic synthesis was combined with a limited descriptive bibliographic summary of the same corpus. The findings suggest a consistent pattern in the literature. AI is most often discussed as shifting disruption management from reactive control toward earlier preparedness by supporting early warning, predictive fidelity, and decision support. Those

Table 12 Operationalising governance, XAI, and digital readiness

Domain	Minimum operational specification	Foundational state	Operational state	Institutionalised state
Governance maturity	Named model owner; logged override protocol; audit trail of recommendation, action, and outcome; pre-agreed ethical criteria for allocation under scarcity	Ownership assigned; no override log	Override log and audit trail in use	Ethical allocation criteria and periodic review of overrides
XAI	A local rationale for the case at hand and a global account of features the model generally prioritizes, delivered inside the DSS at decision speed	Post-hoc verbal explanation after the decision	Local rationale available in the DSS	Local and global explanations available at decision speed
Digital readiness	Integrated master data; timely feeds from planning and logistics systems; managerial data literacy sufficient to interrogate outputs	Fragmented spreadsheets and delayed extracts	Integrated master data with delayed feeds	Timely feeds and literate managers who can contest outputs

reported benefits are neither automatic nor universal. The proposed framework posits that AI-associated effects are channeled through two capability paths, agility in the short horizon and adaptability in the longer horizon, and that governance maturity and digital readiness operate as constraints on whether those paths can operate [21].

The thematic analysis identified five dominant patterns in the literature. Predictive AI functions as a foresight amplifier, improving preparedness by detecting disruption signals earlier and enabling more targeted contingency planning. Prescriptive analytics and digital twins support response-stage agility by reducing the latency between sensing and action. Learning-oriented AI enables longer-horizon adaptability by supporting model retraining, double-loop organizational learning, and simulation-based network redesign. A persistent governance and trust deficit emerges as the central adoption bottleneck: when AI operates as a black box, decision-makers may override recommendations at the critical moment, nullifying realized resilience value. Digital readiness, encompassing integrated data infrastructure, analytics capability, and data literacy, serves as the feasibility precondition without which AI cannot move from prototype to operational resilience. The descriptive bibliographic summary corroborated these thematic findings only qualitatively, by noting the recurrence of predictive analytics and digital twins, of agility and adaptability as proposed mediating constructs, and of governance and interpretable AI as recent terms of art.

7.2 Theoretical contributions

The review offers five bounded theoretical contributions, consistent with the abstract and Sect. 1. It maps AI capability types onto disruption-lifecycle stages rather than treating AI as a homogeneous construct. It combines thematic synthesis with a limited descriptive bibliographic summary of the same corpus. That combination is unusual in this niche, but it is not a bibliometric network analysis. Relative to the reviews in Table 1, the distinctive increment is a conversion architecture in which agility and adaptability are capability paths and in which governance maturity and digital readiness are independently necessary constraints. It discusses XAI as a decision-relevant requirement in disruption settings. It specifies sensing, seizing, and transforming as AI-supported subprocesses that future work can test. None of these contributions is an estimated causal model.

7.3 Practical implications

For practitioners, the central implication is that AI should be deployed as a strategic complement to existing resilience mechanisms rather than as a standalone solution. Organizations seeking to maximize resilience value should prioritize data integration and governance maturity before investing in algorithmic sophistication, implement layered explainability mechanisms that enable both rapid trust calibration and post-event accountability, and develop AI literacy within supply chain leadership and operational teams as a prerequisite for confident action under disruption. For policymakers, the review highlights the need for standardized XAI documentation requirements for supply chain AI applications, cross-industry mechanisms for anonymized disruption data

sharing, and governance frameworks that explicitly assign accountability for high-stakes automated decisions. These ecosystem-level interventions are necessary because many resilience failures are structural and cross-organizational rather than firm-level, requiring coordinated institutional action beyond individual capability development.

7.4 Limitations

Several limitations bound interpretation. The search used three sources (Emerald, Web of Science, and Google Scholar) and is subject to their indexing coverage and to keyword sensitivity; studies using non-standard terminology or appearing in non-indexed outlets may have been missed. The synthesis is English-language only. Publication bias remains a concern because successful applications are more likely to be published than null results or failed implementations. Exact per-database retrieval totals, duplicate counts, stage-specific exclusion counts, search-log dates at the query level, Web of Science index names, the Google Scholar bounding rule, reference-manager software, the number of screeners, and an agreement statistic were not retained and cannot be reconstructed; the paper therefore does not claim PRISMA 2020 compliance and is not presented as a full systematic review. Appraisal was a five-dimensional qualitative reading inspired by JBI, not a scored checklist with study-level numeric grades. The bibliographic component is a limited descriptive summary of the included set; citation networks and keyword-evolution maps were not performed. The evidence base is methodologically heterogeneous, with many conceptual, simulation, and cross-sectional studies and comparatively few longitudinal or cross-industry field evaluations, which limits causal inference. Conclusions should be read as evidence-informed patterns, not as effect-size estimates.

7.5 Future research directions

Future research should move the field from predominantly conceptual and simulation-led propositions toward validated, explainable, and deployable systems. Priority directions include cross-industry empirical validation under real disruption conditions, with outcomes such as time-to-detect, time-to-decide, time-to-recover, and service continuity rather than forecast accuracy alone, and with meaningful non-AI baselines. Longitudinal designs are needed to test whether learning is institutionalized and whether it produces structural resilience improvement rather than only short-horizon agility.

Table 13 Settings where empirical validation of AI-enabled resilience is most needed

Setting	Why is validation needed in the present corpus	Suggested empirical focus
Multi-tier manufacturing	Deep-tier visibility is repeatedly described as weak relative to focal-firm forecasting.	Time-to-detect and time-to-recover versus non-AI baselines
Pharmaceuticals and other highly regulated allocation	High-stakes scarcity decisions carry ethical and legal exposure that the corpus discusses more than it measures.	Governance and XAI under explicit allocation rules
Logistics platforms	Speed of rerouting is central, but field measurement of AI-supported agility remains thin.	Sense-seize latency and service continuity
Small and medium-sized firms with fragmented systems	Digital readiness is the proposed feasibility constraint, yet illustrative implementation examples in the corpus are mostly digitally mature settings.	Whether foundational data investment precedes any resilience gain
Cross-industry comparative designs	The 75 studies that met the inclusion criteria are methodologically heterogeneous and are not a sector census.	Contingency tests of governance maturity and digital readiness as distinct constructs

Digital readiness and governance maturity should be operationalized as distinct, measurable constructs and tested as contingencies. Table 13 records the industry settings in which that validation is most needed on the present evidence. XAI effectiveness should be compared under time pressure on decision speed, override probability, and confidence calibration. DSS architecture, override logging, and human-in-the-loop rules should be treated as part of system performance. Rare-event learning remains an open methodological problem. Ethical and sustainability trade-offs in disruption allocation and in the energy cost of large models should be studied as design constraints, not as afterthoughts. Citation-network and keyword-evolution analyses were not performed in the present study and remain potential directions for future research using retained and reproducible bibliographic export files.

Table 13 lists the industry and organisational settings in which empirical validation is most needed on the present evidence. The table is a gap map derived from the coded corpus and from Appendix Table 14. It is not a ranking of sectors by publication count, and it does not invent a sector census.

7.6 Concluding statement

The reviewed literature suggests that AI can contribute to supply chain resilience when embedded in a governed socio-technical system that combines reliable data, appropriate digital capabilities, explainability, and institutional accountability. However, the available evidence does not establish AI as a necessary or universally foundational component of resilience. Rather, the synthesis identifies recurring associations between AI applications and improved foresight, more rapid operational responses, and learning-oriented structural adaptation. The strength and generalizability of these associations vary across applications and study designs, and the proposed relationships involving structural adaptation and governance conditions require further empirical validation.

Finally, the review indicates that ethical considerations are inseparable from resilience applications because disruption decisions often involve allocation under scarcity. Risks related to opacity, bias, and data governance can create institutional and reputational exposure, reinforcing the need for explainability and governance maturity as operational requirements rather than optional enhancements [54].

Appendix

See Tables14 and 15.

Table 14 Comprehensive synthesis of included studies

Study	Method	SC context	AI technique	AI capability	Resilience dimension	Dynamic capability	Key findings	Challenges	Evidence weight
[4]	Conceptual	Global SC	Not reported	Not reported	Preparedness	Adaptability	Globalization risks	Not reported	Not reported
[5]	Empirical	Global SC	Not reported	Not reported	Response	Not reported	COVID disruptions	Not reported	Not reported
[6]	Review	SC resilience	Not reported	Not reported	All	Not reported	Foundational SCRES concept	Not reported	Not reported
[7]	Conceptual	SC resilience	Not reported	Not reported	All	Not reported	Multidimensional resilience	Not reported	Not reported
[8]	Conceptual	Risk mgmt	ML	Prediction	Preparedness	Agility	Real-time risk detection	Data quality	Low
[9]	Review	Logistics	Technology	Prediction	Preparedness	Agility	Tech improves risk mgmt	Implementation	Low
[10]	Mixed	SCM	AI	Reasoning	Response	Agility	AI improves responsiveness	Integration	Medium
[11]	Empirical	Risk	DL	Prediction	Response	Agility	AI improves agility	Complexity	Low
[12]	Conceptual	SCM	AI	All	All	All	Integrated framework	Implementation	Medium
[13]	Review	Forecasting	Big Data	Prediction	Preparedness	Agility	AI improves demand forecasting	Integration	Low
[17]	Empirical	Airlines	Not reported	Not reported	Preparedness	Not reported	Competitive resources	Not reported	Not reported
[18]	Empirical	SMEs	AI analytics	Prediction	Preparedness	Adaptability	AI builds resilience via DC	Data limits	Low
[19]	Empirical	Sustainability	AI	Prediction	Preparedness	Innovation	AI enhances CSR	Complexity	Low
[20]	Empirical	Suppliers	Digital innovation	Prediction	Preparedness	Innovation	Supplier structure affects innovation	Dependency	Low
[21]	Empirical	Firms	AI	All	All	Innovation	AI enhances adaptability	Complexity	Low

Table 14 (continued)

Study	Method	SC context	AI technique	AI capability	Resilience dimension	Dynamic capability	Key findings	Challenges	Evidence weight
[16]	Conceptual	SCM	AI capabilities	All	All	Agility	AI capability framework	Empirical gap	Low
[22]	Empirical	AI adoption	AI	Interaction	All	Adoption	Trust is key for adoption	Lack of transparency	High
[51]	Review	General	XAI	Interaction	All	Adoption	XAI improves transparency	Complexity	High
[62]	Conceptual	Human-AI	AI models	Interaction	All	Adoption	Human-AI collaboration critical	Trust	Medium
[23]	Conceptual	Governance	AI policy	Interaction	All	Adoption	National AI strategies	Governance gaps	High
[24]	Conceptual	Governance	AI	Interaction	All	Adoption	Governance framework	Policy gaps	High
[25]	Review	SCM	AI	All	All	Adaptability	AI transforms SCM	Skills gap	Medium
[26]	Review	Forecasting	ML	Prediction	Preparedness	Agility	ML improves time series	Generalization	Low
[27]	Conceptual	Risk	AI	Prediction	Preparedness	Agility	AI handles uncertainty	Model limits	Low
[28]	Empirical	Risk analytics	AI/analytics	Prediction	Preparedness	Agility	AI improves risk signal detection	Transition barriers	Low
[31]	Conceptual	Decision support systems (general)	DSS	Reasoning	All	Agility	DSS supports structured and semi-structured decision-making in complex environments	Limited adaptability in traditional DSS	Low

Table 14 (continued)

Study	Method	SC context	AI technique	AI capability	Resilience dimension	Dynamic capability	Key findings	Challenges	Evidence weight
[32]	Review	SC risk management	AI + DSS	Prediction/ Reasoning	Preparedness/ Response	Agility	AI-enhanced DSS improves risk identification and mitigation in supply chains	Data integration and model complexity	Medium
[15]	SLR	SC resilience	AI + Prescriptive analytics	Reasoning	Response/ Recovery	Agility & Adaptability	Prescriptive analytics enhances proactive and reactive resilience strategies	Implementation complexity and data requirements	Medium
[29]	Conceptual/ Empirical	SC disruption management	Digital Twins + AI	Perception/ Prediction	Response/ Recovery	Agility & Adaptability	Digital twins enable real-time monitoring and disruption mitigation	High implementation cost and integration challenges	Medium
[33]	Empirical	SC decision-making	XAI-enabled DSS	Interaction/ Reasoning	Response	Agility	XAI enhances transparency and trust in AI-driven supply chain decisions	Model interpretability versus performance trade-off	High
[34]	Review	Operational research/ SCM	XAI	Interaction	All	Adoption	Provides a comprehensive framework for integrating XAI into OR applications	Lack of standardized XAI evaluation methods	High

Table 14 (continued)

Study	Method	SC context	AI technique	AI capability	Resilience dimension	Dynamic capability	Key findings	Challenges	Evidence weight
[35]	Review	Decision support systems	XAI-based DSS	Interaction/ Reasoning	All	Adoption	XAI-DSS improves interpretability and decision quality	Scalability and usability challenges	High
[36]	Conceptual	Strategy	AI	All	All	Adaptability	AI builds advantage	Limited evidence	Low
[37]	Conceptual	SCM	AI + IoT+Blockchain	All	All	Adaptability	Tech synergy improves resilience	Integration	Medium
[38]	Method	SLR	Not reported	Not reported	Not reported	Not reported	Review methodology	Not reported	Not reported
[39]	SLR	SC resilience	AI	All	All	All	AI strengthens resilience	Fragmentation	Medium
[40]	Method	SLR	Not reported	Not reported	Not reported	Not reported	PRISMA-based review structuring	Not reported	Not reported
[41]	Method	Search strategy	Not reported	Not reported	Not reported	Not reported	Search methodology	Not reported	Not reported
[42]	Method	Research	Not reported	Not reported	Not reported	Not reported	Research methods	Not reported	Not reported
[53]	Method	Research	Not reported	Not reported	Not reported	Not reported	Research onion	Not reported	Not reported
[59]	Method	Appraisal	Not reported	Not reported	Not reported	Not reported	Quality tools	Not reported	Not reported
[58]	Review	Risk	ML	Prediction	Preparedness	Agility	ML enhances risk assessment	Data quality	Low
[50]	Conceptual	Decision	Symbolic AI	Reasoning	Response	Agility	Prescriptive analytics support decisions	Complexity	Medium
[59]	Conceptual	SCM	Generative AI	All	All	Innovation	GenAI enhances capabilities	Governance	Medium
[52]	Conceptual	AI ethics	AI	Interaction	All	Adoption	Transparency problem	Trust	High

Table 14 (continued)

Study	Method	SC context	AI technique	AI capability	Resilience dimension	Dynamic capability	Key findings	Challenges	Evidence weight
[53]	Review	ML	XAI	Interaction	All	Adoption	Explaining black-box models	Interpretability gap	High
[54]	Empirical	Risk mgmt	XAI	Interaction	Response	Agility	XAI builds trust	Implementation difficulty	High
[60]	Conceptual	Optimization	XAI	Interaction	Response	Agility	Explainable forecasting	Complexity	High
[55]	Review	General	XAI	Interaction	All	Adoption	XAI methods overview	Technical complexity	High
[56]	Review	General	XAI	Interaction	All	Adoption	Trustworthy AI needs explainability	Ethical risks	High
[61]	Conceptual	SCM	AI	All	All	Adaptability	AI challenges & strategies	Barriers	Medium
[57]	Empirical	SCM	AI	All	All	Agility	DC mediates AI-resilience	Measurement	Low
[45]	Empirical	SC performance	AI innovation	Prediction	All	Innovation	AI boosts resilience & performance	Readiness	Low
[63]	Conceptual	Sustainability	Big Data/AI	Prediction	Preparedness	Adaptability	AI supports environmental decisions	Data issues	Low
[64]	Conceptual	Risk	AI	Prediction	Preparedness	Adaptability	AI & uncertainty	Model limits	Medium
[65]	Review	Pharma SC	AI	Prediction	Preparedness	Agility	AI improves signal detection	Data limitations	Low
[66]	Conceptual	Governance	AI	Interaction	All	Adoption	Trust & governance linked	Policy gaps	High
[67]	Review	Research systems	AI	Interaction	All	Adoption	AI benefits & risks in research	Governance gaps	High

Table 14 (continued)

Study	Method	SC context	AI technique	AI capability	Resilience dimension	Dynamic capability	Key findings	Challenges	Evidence weight
[14]	SLR	SCM	AI + BDA	Prediction	All	Agility	AI improves resilience	Fragmentation	Low
[68]	Review	Digital SC	AI security	Interaction	Response	Agility	Cyber risks in SC	Security threats	High
[46]	Empirical	Forecasting	DL + SHAP	Prediction	Preparedness	Agility	Interpretable forecasting	Complexity	High
[69]	Conceptual	ESG	AI	Interaction	All	Adoption	AI impacts sustainability	Ethical issues	High
[70]	Empirical	SRM	ML	Prediction	Preparedness	Agility	AI optimizes supplier risk	Data dependency	Low
[71]	Empirical	Risk mgmt	AI systems	All	All	Agility	AI enhances entrepreneurial resilience	Integration issues	Medium
[72]	Conceptual	Insurance SC	Generative AI	Prediction	Preparedness	Innovation	AI improves data processing	Bias	Medium
[73]	Empirical	SC performance	Big Data	Prediction	Preparedness	Agility	Analytics improves performance	Data integration	Low
[30]	Case study	Procurement	RPA	Reasoning	Recovery	Agility	RPA improves efficiency	Cost	Low
[74]	Empirical	Data systems	AI infra	Perception	Preparedness	Adaptability	Data architecture critical	Infrastructure	Medium
[75]	Review	SCM	AI	All	All	Adaptability	AI improves optimization	Integration	Medium
[76]	Empirical	Financial SC	ML	Prediction	Preparedness	Agility	AI improves financial risk control	Data issues	Low
[77]	Conceptual	SCM	AI	All	All	Efficiency	AI improves business performance	Adoption barriers	Low
[48]	Review	SCM	Digital twins	Perception	Response	Agility	DT improves visibility	Cost	Medium

Table 14 (continued)

Study	Method	SC context	AI technique	AI capability	Resilience dimension	Dynamic capability	Key findings	Challenges	Evidence weight
[49]	Empirical	Crisis SC	Data-driven	Prediction	Response	Agility	Data improves resilience	Data fragmentation	Low
[47]	Empirical	Forecasting	Deep Neural Network (DNN)	Prediction	Preparedness	Agility	AI outperforms Autoregressive Integrated Moving Average (ARIMA)	Data needs	Low
[78]	Conceptual	Risk	GenAI	Prediction	Preparedness	Innovation	GenAI in risk management	Uncertainty	Medium

Table 15 Capability-stage taxonomy of AI families used in the synthesis

AI family	Primary resilience stage discussed	Decision role	Illustrative methods in the corpus
Predictive AI	Preparedness	Early warning and targeted buffering	Machine learning and deep learning forecasting; anomaly detection [26–28]
Prescriptive and optimization AI	Response	Constrained action selection	Prescriptive engines and combinatorial allocation [12]
Digital twins and IoT visibility	Response	Situational awareness and what-if evaluation	Digital twins and sensor fusion [12, 29]
Automation (RPA)	Recovery	Execution speed on rule-structured workflows	RPA in purchasing and recovery administration [24, 30]
Learning-oriented AI	Development	Post-event retraining and structural redesign	Retraining and simulation-based exploration [18]
AI-enabled DSS	Cross-stage	Integration of insight, explanation, override, and logging	DSS and XAI workflows [15, 31–35]

Author contributions
A.A. designed the review methodology, supervised the research process, designed and refined the conceptual framework, and substantially wrote, revised and expanded the manuscript. A.H. conducted the literature search, performed data extraction and coding, and drafted the very initial version of the manuscript. N.K. supported data analysis, contributed to the bibliographic observations, and assisted in preparing tables and figures. S.K. provided senior guidance, supervised the research process, contributed to the interpretation of findings, and reviewed the manuscript for intellectual coherence. All authors reviewed and approved the final manuscript.

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