AI-Driven Supply Chain Management Systems for Resilient and Sustainable Operations: The Role of Digital Twins, IoT, and Predictive Analytics

Koo Kee Wai[1], Lee Man Yi[2], Saw Tsu Koon[3], Normal Mat Jusoh[4]

[1,2,3,4]Azman Hashim International Business School, Universiti Teknologi Malaysia

DOI: https://doi.org/10.51244/IJRSI.2026.1306000468

Received: 01 July 2026; Accepted: 06 July 2026; Published: 17 July 2026

ABSTRACT

Global supply chains are passing through a period of unusual volatility, in which lean, efficiency-first models have repeatedly failed to absorb systemic shocks such as pandemics and geopolitical disruption. This paper reviews how artificial intelligence (AI) and three of its closest enabling technologies, namely the Internet of Things (IoT), digital twins, and predictive analytics, are being used to build supply chains that are both more resilient and more sustainable. Drawing on peer-reviewed journal research published within the last five years, the study brings together streams of work that are usually examined separately and asks how they fit together within the emerging vision of Industry 5.0 and increasingly autonomous supply chains. The synthesis indicates that AI shifts supply chain management from a reactive posture to an anticipatory one. IoT supplies the real-time visibility that supports proactive risk management, predictive and prescriptive analytics turn that data into early warning of demand shifts and disruption and into recommended action, digital twins allow managers to stress-test recovery options before acting on them, and blockchain adds a layer of trust to the data exchanged between partners. The review finds that the value of these technologies appears when they are integrated into a coherent, layered architecture rather than adopted in isolation, and that their contribution to resilience runs through underlying capabilities such as visibility, flexibility, and collaboration rather than through the technology alone. It also examines the obstacles that continue to slow adoption, including implementation cost, cybersecurity exposure, a persistent digital skills gap, interoperability with legacy systems, and the limited interpretability of complex models. The paper proposes a layered reference architecture for autonomous supply chains and sets out recommendations for practitioners and policymakers seeking a technology-driven, human-centric, and environmentally responsible supply network.

Keywords: Artificial Intelligence; Digital Twins; Internet of Things; Predictive Analytics; Supply Chain Resilience; Sustainability; Industry 5.0

INTRODUCTION

Global supply chains form the basic structure of international commerce, moving goods and services through diversified and tightly connected markets. The environment in which they operate, however, has become one of radical uncertainty. The COVID-19 pandemic disrupted a large majority of global supply chains and exposed the fragility of a lean, efficiency-only approach, and it was quickly followed by geopolitical conflict and climate-related shocks (El Baz & Ruel, 2021; Rahman, Paul, Shukla, Agarwal, & Taghikhah, 2022). The disruptions did not remain local. They travelled through tightly linked networks and revealed how thin the visibility of many firms turned out to be once their supply chains came under strain. As demand has grown more volatile and environmental expectations have risen, firms have placed new emphasis on resilience, the ability to anticipate, absorb, and recover from disruption, and on sustainability, including the integration of environmental and social considerations into core operations (Ivanov, 2024; Marinagi, Reklitis, Trivellas, & Sakas, 2023).

Much of conventional supply chain management was built for a steadier world. It leans on historical records and on analysing problems after they have already happened, which leaves firms a step behind fast-moving disruption. That reactive habit fits poorly with an environment of nonlinear interactions, high-velocity data, and shrinking decision windows. The factor now driving change is digital transformation. AI provides the intelligence that helps firms anticipate and manage risk, while IoT acts as the sensory network that supplies real-time visibility of physical operations (Sallam, Mohamed, & Wagdy Mohamed, 2023; Nozari, Szmelter-Jarosz, & Ghahremani-Nahr, 2022). Digital twins extend these capabilities by creating high-fidelity virtual replicas of physical supply chain assets, allowing managers to test what-if scenarios without disturbing physical flows (Ivanov & Dolgui, 2021; Guo & Mantravadi, 2025). Predictive and prescriptive analytics translate the resulting data into foresight and recommended action (Smyth, Dennehy, Fosso Wamba, Scott, & Harfouche, 2024; Aljohani, 2023). Each of these technologies has its own substantial literature, and each has been shown to deliver value in particular settings. What has received far less attention is how they behave together, even though in practice they are deeply interdependent. A digital twin without IoT data is a static model; IoT data without analytics is noise; analytics without a twin to coordinate its outputs struggles to inform network-level decisions. The interdependence is the reason this review treats the four technologies as a system rather than as a list.

These technologies are seldom discussed in tandem, yet a recurring argument in the literature is that their real value lies in synergistic integration rather than isolated deployment (Culot, Podrecca, & Nassimbeni, 2024; Richey, Chowdhury, Davis-Sramek, Giannakis, & Dwivedi, 2023). The same argument sits at the heart of the shift from Industry 4.0, with its focus on automation, towards Industry 5.0, which places resilience, sustainability, and human-centricity at the centre and treats advanced technology as a partner to human judgement rather than a replacement for it (Ivanov, 2023). The transition towards more autonomous supply chains depends on connecting physical operations and digital intelligence within a single, coherent framework, and on doing so in a way that keeps people in the loop.

Despite the rapid growth of research on each technology, the field remains fragmented. Studies tend to examine a single technology in a single setting, and the relative weight of evidence, the leading sources of knowledge, and the barriers to adoption have not been pulled together in a way that supports both scholars and practitioners (Pournader, Ghaderi, Hassanzadegan, & Fahimnia, 2021; Riahi, Saikouk, Gunasekaran, & Badraoui, 2021). Earlier systematic reviews mapped the breadth of AI techniques across supply chain functions and traced the field from Industry 4.0 towards more recent paradigms (Toorajipour, Sohrabpour, Nazarpour, Oghazi, & Fischl, 2021; Samuels, 2025), but comparatively little work reads the four technologies together and asks how they jointly serve resilience and sustainability. That gap is the focus of this review.

This paper synthesises recent peer-reviewed research on AI-driven supply chain management for resilient and sustainable operations, with particular attention to the roles of digital twins, IoT, and predictive analytics, and to the transition towards Industry 5.0 and autonomous supply chains. It pursues four aims: to set out how these technologies are conceived and applied; to explain how they contribute to resilience and sustainability; to identify the obstacles that constrain adoption; and to propose an integrated architecture together with practical recommendations. Its contribution is to connect streams of work that are usually treated separately, to weigh the optimistic findings of applied studies against the more cautious conclusions of recent reviews, and to translate the synthesis into guidance for managers and policymakers. The remainder of the paper reviews the literature by theme, describes the review method, presents and discusses the synthesis, and closes with conclusions and recommendations.

LITERATURE REVIEW

The review is organised by theme. It begins with the goals of resilience and sustainability, then traces how AI has entered supply chain research and the methods it brings. It takes each enabling technology in turn, IoT, predictive analytics, digital twins, and the blockchain layer that often accompanies them, before considering their combined impact and the newer frontier of generative AI.

Resilience and sustainability as the goals

Supply chain resilience describes a network's ability to prepare for disruption, absorb it, and recover while keeping operations running. The concept has matured from a narrow concern with robustness into a broader, more dynamic idea that includes the capacity to adapt and, in extreme cases, to survive. Ivanov (2024) distinguishes between a product-centred and a network-centred view of resilience, a reminder that resilience operates at several levels at once rather than as a single property. El Baz and Ruel (2021), drawing on survey evidence from the early pandemic, show that risk management practices help firms preserve both resilience and robustness, but only when they are actually in place, which many were not. Rahman et al. (2022), reviewing resilience initiatives and strategies, find a consistent emphasis on visibility, flexibility, and collaboration, the very capabilities that digital technologies are well placed to strengthen. Their review also organises the many strategies firms use into proactive measures, taken before disruption to reduce vulnerability, and reactive measures, taken afterwards to speed recovery, and it observes that the most resilient firms invest in both. This distinction matters for the present review, because AI and its enabling technologies contribute to each. They support proactive resilience by improving visibility and early warning, and reactive resilience by accelerating detection, diagnosis, and response once a disruption hits.

Sustainability is the second goal, and it overlaps with resilience more than is often recognised. Practices that cut waste and use resources more efficiently improve environmental performance while also buffering firms against shortages and price swings. Ivanov (2023) makes the connection explicit through an Industry 5.0 framework that folds resilience, sustainability, and human-centricity into a single perspective, arguing that these aims should be optimised together rather than pursued in turn. Marinagi et al. (2023) reinforce the point from the technology side, showing that Industry 4.0 tools support both resilience and sustainability by improving shared underlying capabilities. The literature therefore frames the two goals not as competitors but as two faces of a well-run, data-informed supply chain, which is the perspective this review adopts.

The evolution towards Industry 5.0 and human-centricity

The framing of advanced supply chains has moved beyond the automation focus of Industry 4.0 towards a model that is human-centric, resilient, and sustainable. Industry 5.0 does not discard the technologies of its predecessor but reorients them around human goals, treating AI and its enabling tools as means of supporting human judgement rather than supplanting it (Ivanov, 2023). For supply chains, this reframing matters in practical terms. It positions analytics and automation as partners in decision-making, and it implies that the organisational and human conditions for adoption, including skills and trust, are as important as the technology itself. Richey et al. (2023), in a primer and roadmap for the field, describe supply chains in which human-machine collaboration, rather than full automation, drives decisions in complex and uncertain environments, and they call for research that takes this collaboration seriously rather than assuming technology will simply replace human work. The human-centric framing also carries a practical warning. Systems that sideline human judgement can fail in ways that are hard to anticipate, particularly when conditions move outside the range the models were trained on, which is precisely what happens during the disruptions that resilience is meant to address. Keeping people in the loop is therefore not a concession to tradition but a source of robustness, since human operators can recognise when a model is out of its depth and intervene. The Industry 5.0 vision, in this reading, is less a rejection of automation than a more mature account of where automation helps and where human oversight remains essential.

The growth of AI research in supply chains

AI has moved from a curiosity to a strategic capability in supply chain management, and the arc is visible in the review literature itself. Toorajipour et al. (2021) survey the field across logistics, marketing, supply chain, and production, and find that AI techniques have spread well beyond forecasting into a wide range of subfields, while gaps remain in others. Pournader et al. (2021) map a large body of journal articles and use co-citation analysis to reveal the clusters of knowledge that have formed, and Riahi et al. (2021) provide a complementary bibliometric picture that points to promising future directions. Samuels (2025) traces the integration of AI across successive industrial paradigms, while Culot et al. (2024) review empirical studies specifically and caution against inflated expectations, arguing that the field needs a sober reading of where AI actually stands before stronger theory can be built. Shahzadi, Jia, Chen, and John (2024) round out this picture by reading adoption through an extended technology-organisation-environment lens, showing that the drivers and barriers are technological, organisational, environmental, and human all at once. Taken together, these reviews establish AI as a mainstream concern while making clear that the evidence is thicker in some functions, such as forecasting, than in others, such as governance and sustainability.

Theoretical lenses on AI adoption

Beyond cataloguing techniques and applications, the literature has begun to ask why some firms extract value from AI while others do not, and it answers the question through several theoretical lenses. Shahzadi et al. (2024)

read adoption through an extended technology-organisation-environment framework, which treats the decision to adopt as the product of technological readiness, organisational capacity, and environmental pressure, with a human dimension layered on top. Dubey et al. (2022) adopt a practice-based view, arguing that the value of an analytics culture lies not in the tools themselves but in the routines and practices through which people use them. Dubey et al. (2023) move to a dynamic-capabilities perspective, in which the ability to sense change, seize opportunities, and reconfigure resources explains why digital capability translates into resilience for some firms and not others, with the wider institutional environment acting as a moderating condition. Jackson (2024) frames generative AI through the resource-based view, treating distinct AI capabilities as resources that can become sources of advantage when they are rare, valuable, and difficult to imitate. These lenses converge on a common message that runs throughout this review. Technology is necessary but not sufficient, and the organisational and human conditions that surround it largely determine whether it delivers.

AI techniques and methods

It helps to be specific about what AI brings, because the term covers a family of methods with different strengths. Machine learning, the workhorse of the field, learns patterns from data without being explicitly programmed. Supervised learning, trained on labelled examples, drives most forecasting and classification work, from demand prediction to fault diagnosis. Unsupervised learning finds structure in unlabelled data and supports tasks such as segmenting suppliers and spotting anomalies. Deep learning, built on multilayer neural networks, has extended these capabilities to images and to sequential data, which matters for visual inspection and time-series forecasting. Douaioui, Oucheikh, Benmoussa, and Mabrouki (2024), reviewing machine learning and deep learning for demand forecasting, show that recurrent and convolutional architectures such as long short-term memory and hybrid models now dominate the most accurate forecasting approaches, while Babai, Boylan, and Rostami-Tabar (2022) examine how these methods handle the aggregation and hierarchy that characterise real supply chains. Reinforcement learning takes a different path, learning good decisions through interaction with a changing environment, which suits adaptive control problems such as replenishment and routing. Each method carries its own demands. Supervised learning needs labelled data, which is often scarce for rare events such as disruptions; unsupervised learning can surface patterns but leaves their interpretation to the analyst; deep learning is powerful but data-hungry and computationally heavy; and reinforcement learning requires a faithful model of the environment in which to learn. These trade-offs explain why no single method dominates and why hybrid approaches, which combine the strengths of several techniques, recur across the most accurate studies. Generative AI, the newest entrant, raises fresh possibilities and fresh questions (Jackson, 2024). The point of naming these methods is not taxonomy for its own sake but to make clear that the value of AI in supply chains depends on matching the method to the problem, and on having the data and skills that the chosen method requires.

Big data and the analytics foundation

Underneath every AI application sits data, and the character of that data shapes what is possible. Modern supply chains generate information of growing volume, variety, and velocity, from point-of-sale transactions and enterprise systems to the continuous streams produced by connected sensors. This abundance is an opportunity and a burden at once. It is an opportunity because rich data allows models to learn subtle patterns that simpler methods miss, and a burden because much of the data is fragmented across systems, inconsistent in format, and incomplete where it is most needed, particularly for the rare disruptive events that resilience is meant to address. Dubey et al. (2022) argue that the decisive factor is not the volume of data a firm holds but the culture through which it uses that data, since an analytics-oriented culture turns raw information into agile and resilient action, while data without such a culture simply accumulates. Aljohani (2023) shows how predictive analytics applied to real-time data supports the rapid mitigation of risk, but only where the data pipeline is reliable enough to act upon. The lesson that runs through this work is that data foundations are not a preliminary step to be completed before the interesting analysis begins, but a continuing investment that determines how far the analysis can go. Firms that treat data quality, integration, and governance as ongoing priorities are better placed to benefit from every layer of technology that sits above the data, while those that neglect these foundations find that even sophisticated models underperform.

IoT and RFID: the foundation of visibility

The Internet of Things provides the real-time data streams on which a data-driven supply chain depends. IoT-enabled devices, including radio-frequency identification tags, allow granular tracking of inventory, the condition of shipments such as temperature in food and pharmaceutical chains, and the location of assets (Sallam et al., 2023). This visibility reduces both stockouts and overstocking, which supports sustainability goals by minimising waste (Marinagi et al., 2023). Nozari et al. (2022) examine the combination of AI and IoT, sometimes termed the Artificial Intelligence of Things, in fast-moving consumer goods, and show that the value of sensing is realised only when analytical capability is laid over the data it produces. They also document the difficulties that accompany large IoT deployments, including cybersecurity exposure, the cost of devices and integration, and the challenge of making heterogeneous systems interoperate. The literature is consistent on the central point: a stream of readings is useful only to the extent that models can interpret it, which directs attention to analytics. It is also worth noting how IoT changes the texture of supply chain management. Where managers once relied on periodic reports and estimates, connected sensors offer a continuous, granular picture of conditions as they unfold, which compresses the time between an event and its detection. This shift from periodic to continuous visibility is what makes proactive management possible in the first place, since a risk that is seen early can be managed, while a risk that surfaces only in a monthly report has often already done its damage. The value of IoT, then, lies not merely in collecting more data but in shortening the distance between the physical world and the decisions taken about it.

Predictive and prescriptive analytics

Predictive analytics uses historical data and machine learning to forecast demand, anticipate disruption, and identify likely points of failure (Aljohani, 2023). Demand forecasting remains the most mature application, and it is also where the methodological literature is richest. Accurate forecasts matter because errors propagate. Small distortions at the point of sale amplify as they move upstream through a multi-tier network, the well-known bullwhip effect, producing excess inventory in some places and shortages in others. Better forecasts dampen this amplification, which is why forecasting sits at the foundation of both efficiency and resilience. Babai et al. (2022) show that the choice between aggregating demand and forecasting at a detailed level has real consequences for accuracy, and that the right choice depends on the structure of the particular chain. Douaioui et al. (2024) document the steady migration from classical statistical methods towards deep learning models such as long short-term memory and convolutional networks, which capture nonlinear and seasonal patterns more effectively, and they note that hybrid models often outperform any single approach. Prescriptive analytics goes a step further by recommending specific actions to mitigate risk before it materialises, and AI is now applied across supply chain risk management more broadly, from early disruption sensing to supplier risk assessment (Deiva Ganesh & Kalpana, 2022). Smyth et al. (2024), reviewing AI research in highly ranked operations journals, show that prescriptive analytics is increasingly seen as a route to resilient supply chains, while also cautioning that the evidence is fragmented across technologies and contexts. The trajectory of the field runs from describing the past, to predicting the future, to prescribing action, and recent work is beginning to explore the role of generative AI at this frontier (Jackson, 2024).

Digital twins and simulation

A digital twin is a dynamic virtual representation of a physical system, kept synchronised through real-time IoT data. In supply chain management, digital twins enable stress-testing and scenario simulation, letting managers visualise how a disruption would propagate through inventory and cash flow before it occurs (Ivanov & Dolgui, 2021). Unlike static models, a twin provides an iterative feedback loop between the physical and virtual worlds, so that the model updates as conditions change and managers can rehearse responses in a safe environment. Guo and Mantravadi (2025), reviewing digital twins in lean supply chains, find that applications concentrate in plan, make, and delivery processes, with sourcing and return processes far less explored, and that monitoring remains more common than the richer predictive and prescriptive uses the technology promises. Their analysis, organised around the supply-chain operations reference processes, also identifies two areas where digital twins add particular value, namely improving coordination across the network and strengthening resilience against disruptions such as the pandemic and geopolitical shocks. Roman et al. (2025) reach a similar conclusion, noting that the greatest gains come when digital twins are integrated with IoT, AI, and blockchain rather than deployed alone, and Riad, Naimi, and Okar (2024) propose a conceptual framework for embedding AI within supply chain operations that places the digital twin at the centre of a continuous sense-analyse-respond loop. The recurring message is that the integrating promise of the digital twin, its ability to coordinate the whole network, is still only partly realised, and that the technology is most powerful not as a standalone simulator but as the layer that ties sensing and analytics into a single, navigable picture of the chain.

Blockchain and the question of data trust

None of the technologies above works without data, and data that crosses organisational boundaries raises the question of trust. Blockchain has become the most discussed answer. By maintaining an immutable, shared record, it can support transparency and accountability across partners, which matters for verifying ethical sourcing and for tracing goods through complex chains. Saurabh and Dey (2021) examine blockchain adoption and architecture for sustainable agri-food chains, where provenance and food safety make traceability especially valuable, and they show that the technology works best when combined with IoT and analytics rather than on its own. Their work points to a wider pattern. Blockchain rarely operates alone; it pairs with IoT, which supplies the data to be recorded, and with smart contracts, which automate agreements between partners once recorded conditions are met. In a food or pharmaceutical chain, this combination can document the journey of a product from origin to shelf, flag deviations in temperature or handling, and settle transactions without manual reconciliation. The enthusiasm is tempered by evidence on adoption. Kouhizadeh, Saberi, and Sarkis (2021) analyse the barriers that hold sustainable blockchain adoption back, locating them in intra- and inter-organisational resources, technological limits, and external relationships, and they note that the benefits accrue only when enough partners participate, which creates a collective-action problem absent from single-firm technologies. The recurring lesson is that blockchain's value depends less on the technology than on the willingness of partners to share data and align incentives, the same condition that integration with AI and IoT also requires.

Agility, sustainability, and the synergistic impact

Agility refers to the speed and flexibility with which a supply chain responds to change. The empirical literature links digital capability to agility and resilience, though it does so through indirect mechanisms rather than crediting the technology alone. Dubey et al. (2022) find that an AI-driven big data analytics culture strengthens agility and resilience in humanitarian operations, where conditions are hardest to predict, and Dubey et al. (2023) connect dynamic digital capabilities to resilience, with the effect shaped by the wider institutional context such as government effectiveness. Marinagi et al. (2023) make the mechanism explicit, arguing that Industry 4.0 technologies do not improve resilience directly but strengthen its underlying elements, including flexibility, visibility, collaboration, and information sharing. These digital investments also translate into sustainability gains, for instance through optimised energy use and the verification of ethical sourcing, where blockchain integration supports transparency and traceability (Saurabh & Dey, 2021; Kouhizadeh et al., 2021). The consistent conclusion is that technology creates value through the agile and sustainability-oriented practices it enables, which is why the human and organisational conditions for adoption matter so much.

Generative AI and the frontier

The newest entrant in the field is generative AI, and it is only beginning to be mapped. Jackson (2024) proposes a capability-based framework that examines how generative AI and the wider family of AI capabilities, including learning, perception, prediction, interaction, adaptation, and reasoning, might affect a range of supply chain and operations decisions, from demand forecasting and inventory management to supply chain design. The framework is forward-looking rather than a record of established practice, which is appropriate for a technology at an early stage. It signals both the promise of generative models, in handling unstructured information and supporting human decision-makers, and the open questions that surround them, including reliability, interpretability, and governance. There is a particular tension here that the field will need to resolve. Generative models are at their most useful when they handle ambiguity and produce fluent, plausible outputs, yet supply chain decisions often demand exactly the opposite, namely outputs that are correct, auditable, and consistent. A forecast or a routing decision that is plausible but wrong can be more dangerous than an obvious error, because it is more likely to be trusted. For this reason, the early literature tends to position generative AI as an assistant to human experts rather than an autonomous decision-maker, and to stress the importance of keeping a person accountable for consequential decisions. The frontier of the field is therefore moving quickly, and the cautious reading offered by recent reviews applies with particular force to claims about generative AI.

METHODOLOGY

Research design

This study is an integrative review of the recent peer-reviewed literature on AI-driven supply chain management for resilient and sustainable operations. An integrative review is appropriate because the objective is to connect several technology streams that are usually studied separately and to build a coherent account of how they work together, rather than to test a single hypothesis. The approach draws together conceptual frameworks, prior systematic and bibliometric reviews, and applied studies, and reads them against one another to identify points of agreement, tension, and gaps. It is well suited to a fast-moving field in which the most useful contribution is a clear synthesis rather than another narrow result.

Search strategy and selection

The review concentrates on peer-reviewed journal articles, identified through academic databases including Scopus and Web of Science and through citation tracing of key papers. The search combined a technology set of terms, such as artificial intelligence, machine learning, digital twin, Internet of Things, and predictive analytics, with a supply chain set of terms, such as supply chain, logistics, resilience, and sustainability, using Boolean operators to capture the intersection of the two. In keeping with the aim of describing the current state of a fast-moving field, the review was restricted to work published within the last five years, from 2021 onward. This window is deliberate. The capabilities of AI, the maturity of digital twins, and the data infrastructure that supports them have all advanced quickly, and evidence drawn from earlier periods can misrepresent what is now possible. Confining the review to recent work keeps the synthesis current, although it carries the trade-off of giving less weight to the foundational studies that shaped the field, whose core ideas are nonetheless reflected in the recent literature that builds on them.

Articles were included when they substantively addressed AI or one of its enabling technologies within a supply chain, logistics, or operations setting, and when they engaged with resilience, sustainability, or related performance outcomes. Conference papers, editorials, book chapters, and non-peer-reviewed material were excluded so that the synthesis rested on evidence that had already passed journal review, and studies that mentioned the technologies only in passing, without a substantive application, were set aside during screening. Particular weight was given to recent systematic and bibliometric reviews, both as sources of evidence and as points of comparison for the present synthesis, and to applied studies that reported concrete outcomes in identifiable sectors.

To make the review process transparent and reproducible, the search protocol was defined in advance. The primary databases were Scopus and Web of Science, chosen for their broad and rigorous coverage of business, management, and engineering research, and these were supplemented by targeted citation tracing of highly cited papers. The search combined two blocks of terms using Boolean operators, in the form (“artificial intelligence” OR “machine learning” OR “digital twin” OR “Internet of Things” OR “predictive analytics” OR “blockchain”) AND (“supply chain” OR “logistics” OR “operations”) AND (“resilience” OR “sustainability” OR “agility” OR “disruption”). The search was applied to the title, abstract, and keyword fields, and was limited to peer-reviewed journal articles written in English and published between 2021 and 2026.

The inclusion criteria were as follows:

- Peer-reviewed journal articles published between 2021 and 2026.
- Written in English.
- Addressing artificial intelligence or one of its enabling technologies, namely IoT, digital twins, predictive analytics, or blockchain, within a supply chain, logistics, or operations context.

- Engaging substantively with resilience, sustainability, or a related performance outcome.

The exclusion criteria were as follows:

- Conference papers, editorials, book chapters, theses, and non-peer-reviewed or grey literature.
- Articles that mentioned the technologies only in passing, without a substantive supply chain application.
- Studies published before 2021, so that the synthesis stays focused on the current state of a fast-moving field.
- Publications not available in full text.

The retrieved records were then processed in four stages, following the logic of established review protocols. In the identification stage, records were gathered from the two databases and from citation tracing. In the screening stage, duplicates were removed and titles and abstracts were assessed against the inclusion criteria. In the eligibility stage, the full texts of the remaining articles were read in detail and judged for relevance and quality. In the inclusion stage, the studies that met every criterion were carried forward into the thematic synthesis. Priority was given to recent systematic and bibliometric reviews and to applied studies reporting concrete outcomes, so that the final set balanced breadth of coverage with depth of evidence.

Analysis

The selected literature was analysed thematically. Each article was examined for the role it assigned to a given technology, the sector or setting it addressed, the outcomes it reported for resilience and sustainability, and the challenges it identified. The themes were then read against one another and assembled into the integrated account presented in the next section, including a layered reference architecture and a structured summary of the principal barriers. Care was taken throughout to set the optimistic findings of applied studies beside the more cautious conclusions of systematic reviews, since the contrast between the two is itself an important result. Where studies disagreed, the review reports the disagreement rather than smoothing it over, on the view that an honest account of an unsettled field is more useful than a falsely tidy one. The synthesis was also checked for balance across the four technologies and the goals of resilience and sustainability, so that the account does not over-represent the better-studied areas, such as forecasting, at the expense of the thinner ones, such as governance. Because the study works with published secondary literature and involves no human participants or primary data collection, its central methodological obligations are transparency about how sources were selected and the accurate citation of every source. The main limitation of the approach is that an integrative review depends on the judgement of its authors and on the quality of the literature it draws upon, and it does not claim the exhaustive coverage of a formal systematic review or meta-analysis.

RESULTS AND DISCUSSION

This section draws the themes together. It sets out a layered architecture for autonomous supply chains, examines the reported impact on performance and resilience, reviews how the evidence varies by sector, names the principal barriers to adoption, offers an integrated reading, and identifies directions for further research.

A layered architecture for autonomous supply chains

Reading the literature together suggests that intelligent, increasingly autonomous supply chains can be understood as a layered architecture, in which each technology occupies a distinct layer and depends on the others. The synthesis points to five layers. A data acquisition layer gathers real-time information from IoT sensors, RFID, and enterprise systems (Sallam et al., 2023; Nozari et al., 2022). An intelligence and analytics layer applies AI and machine learning to turn that raw data into predictive and prescriptive insight (Aljohani, 2023; Smyth et al., 2024). A digital twin layer provides virtual replicas for risk assessment and what-if simulation (Ivanov & Dolgui, 2021; Guo & Mantravadi, 2025). An execution and automation layer carries decisions into action across physical operations. A feedback and learning loop monitors outcomes and feeds them back so that the system continues to improve over time (Roman et al., 2025; Riad et al., 2024). The architecture is best understood as a reference model rather than a finished blueprint, since most organisations implement only parts of it, but it makes clear why the layers depend on one another and why partial implementations often underdeliver. Table 1 summarises the role of each technology, its contribution to resilience and sustainability, and the main challenges associated with it.

Table 1. The technology layers of AI-driven supply chain management.

Technology	Primary role	Contribution to resilience and sustainability	Main reported challenges
Internet of Things and RFID	Real-time sensing of assets and flows	Visibility, traceability, condition monitoring, waste reduction	Cybersecurity, interoperability, adoption cost
Predictive and prescriptive analytics	Turning data into foresight and recommended action	Demand forecasting, disruption prediction, risk mitigation	Data quality and scarcity, model transferability
Digital twins	Living model for simulation and coordination	Scenario testing, stress-testing, recovery planning	Concentration on monitoring; limited prescriptive use
Blockchain	Trusted, shared record across partners	Transparency, traceability, ethical sourcing, accountability	Adoption barriers, incentive alignment, scalability
Artificial intelligence (learning layer)	Connecting the layers and enabling adaptation	Anticipatory and increasingly autonomous decision-making	Interpretability, governance, skills, energy footprint

Source: Authors, compiled from the reviewed literature.

Impact on performance and resilience

The empirical literature consistently associates AI and digital-twin capability with greater agility and resilience, although it attributes the effect to indirect mechanisms rather than to the technology alone. Dubey et al. (2022) show that an analytics-oriented culture supports agility and resilience precisely where uncertainty is highest, and Dubey et al. (2023) find that dynamic digital capabilities strengthen resilience, conditioned by the wider institutional environment. Marinagi et al. (2023) make the mechanism explicit, demonstrating that Industry 4.0 technologies act on resilience by improving the underlying capabilities of flexibility, visibility, collaboration, and information sharing rather than by acting on resilience directly. This indirect relationship is easy to misread. A casual observer might conclude that since the technology does not improve resilience directly, it does not matter much, but the opposite is closer to the truth. Because the technology works through capabilities that are themselves valuable across many situations, its benefits are broad and durable rather than narrow and contingent on a particular type of shock. A chain that has become more visible and more flexible is better prepared for disruptions it has never seen before, which is exactly the property that matters most in an uncertain world. This indirect pathway matters for practice, because it implies that buying technology is not enough on its own. The value appears only when the technology is embedded in agile and sustainability-oriented ways of working, which depends in turn on organisational readiness, data quality, and skills (Shahzadi et al., 2024). The same logic explains why otherwise similar investments produce very different results across firms, and why the cautious reviews attribute many disappointments to implementation rather than to the technology itself.

Conditions for successful adoption

If technology alone does not deliver, it is worth asking what does. The literature points to a consistent set of conditions. The first is data. Predictive models, digital twins, and blockchain records all depend on data that is timely, accurate, and shared, and the absence of such data is among the most frequently cited reasons that projects stall (Nozari et al., 2022). The second is skills. Realising value requires people who can build, interpret, and act on analytical outputs, and the shortage of such people, often described as a digital skills gap, slows adoption even where the technology is sound (Shahzadi et al., 2024). The third is organisational readiness, including leadership commitment, a willingness to redesign processes around new capabilities, and a culture that treats data as a basis for decisions rather than a by-product of operations (Dubey et al., 2022). The fourth is integration, since the value of any one technology grows when it is connected to the others, and falls when it sits in a silo (Culot et al., 2024). A fifth, easy to overlook, is trust, both in the models, which must be interpretable enough to act upon, and between partners, who must be willing to share the data that network-wide systems require (Nimmy et al., 2022; Kouhizadeh et al., 2021). These conditions are mutually reinforcing, which is why firms that do well tend to do well across several of them at once, and why piecemeal efforts that address only one rarely move the needle. The interdependence has a practical consequence for sequencing. Because the conditions support one another, the most effective adoption paths tend to build them in parallel rather than in strict sequence, pairing each new technical capability with the data, skills, and process changes needed to use it. A firm that installs sensors without the analytics to interpret them, or deploys a model without training the people who must act on its outputs, will see little return, not because the technology failed but because the surrounding conditions were missing. This helps explain a pattern noted across the reviews, namely that ambitious technology programmes often disappoint while modest, well-integrated ones succeed.

Sector applications and uneven coverage

The value of these technologies is not uniform but depends on the dominant source of difficulty in a given chain. In food and agriculture, where goods perish and provenance matters, the combination of IoT sensing, digital-twin analysis, and blockchain traceability addresses problems that are acute and specific. Burgos and Ivanov (2021) use a digital twin to analyse food retail resilience during the pandemic and derive concrete improvement directions, while Nayal, Raut, Queiroz, Yadav, and Narkhede (2021) examine the suitability of AI and machine learning for agriculture supply chains under disruption, and Saurabh and Dey (2021) show how blockchain supports sustainable agri-food traceability. The food sector is instructive precisely because its difficulties are vivid. A delayed shipment can mean spoiled produce, a break in the cold chain can render goods unsafe, and a contamination event can require rapid, accurate tracing of affected products back through the chain. Each of these problems maps neatly onto one of the technologies reviewed here, which is why food and agriculture have become among the most active settings for combined IoT, analytics, digital-twin, and blockchain deployment. In fast-moving consumer goods, the integration of AI and IoT supports responsiveness across high-volume operations (Nozari et al., 2022). In healthcare and pharmaceuticals, where reliability is a matter of patient safety, intelligent systems that combine blockchain, IoT, and machine learning have been applied to vaccine and cold-chain management to reduce uncertainty and safeguard product integrity (Hu, Xu, Liu, & Lim, 2023). In humanitarian operations, where uncertainty is extreme, an analytics culture and designed redundancy have both been linked to agility and resilience (Dubey et al., 2022; Stewart & Ivanov, 2022). In manufacturing and logistics, the emphasis falls on demand planning, condition monitoring, and the simulation of production and distribution flows, areas where the methodological literature on forecasting and digital twins is most developed (Babai et al., 2022; Guo & Mantravadi, 2025). The common thread across these sectors is that the technologies earn their place by addressing a difficulty that is specific and costly in that setting, whether perishability in food, safety in healthcare, volatility in consumer goods, or extreme uncertainty in humanitarian relief.

At the same time, the coverage of the literature is uneven, and the gaps are themselves a finding. Guo and Mantravadi (2025) note that sourcing and return processes remain underexplored relative to plan, make, and delivery, and Iftikhar, Ali, Arslan, and Tarba (2024) observe that the evidence on data analytics and resilience, while growing quickly, is still concentrated in a limited set of themes and methods. Demand forecasting, by contrast, is comparatively well served, with a mature methodological literature on machine learning and deep learning approaches (Babai et al., 2022; Douaioui et al., 2024). This unevenness has a practical cost. When research concentrates on the processes and sectors that are easiest to study or most commercially visible, managers working in the neglected areas, such as reverse logistics or sourcing in less prominent industries, are left with thinner guidance precisely where they may need it most. The practical implication is that firms should match technology to the specific risks of their own chains rather than adopt a fixed template, and researchers should direct attention to the processes and sectors that current work has neglected.

Illustrative applications of the architecture

The value of the layered architecture becomes clearer when it is read against real published applications, each of which activates several layers at once. In food retail, Burgos and Ivanov (2021) built a digital-twin model of a supply chain during the COVID-19 pandemic and used it to simulate how disruptions to demand and supply would ripple through the network. Their study shows the sensing, analytics, and digital-twin layers working together, as real-time data feeds a virtual replica in which managers can test recovery options, such as adjusting order policies, before applying them to the physical chain.

In healthcare, Hu et al. (2023) describe an intelligent vaccine supply chain that combines blockchain, IoT, and machine learning. Here the sensing layer monitors the cold chain, the blockchain layer secures and authenticates the record of each vaccine's journey, and the analytics layer supports decisions that protect product integrity. The case shows how the trust layer becomes decisive in a setting where a single lapse can compromise patient safety.

In humanitarian relief, Dubey et al. (2022) show that organisations with a strong analytics culture achieved greater agility and resilience during crises, while Stewart and Ivanov (2022) demonstrate how deliberately designed redundancy supports recovery when demand is unpredictable. Taken together, these cases illustrate the central claim of the architecture, namely that the layers deliver most when they operate together, and that the mix which matters most shifts with the dominant difficulty of the sector, whether that is perishability, safety, or extreme uncertainty.

From technology to performance indicators

A practical question for any firm is how to tell whether an investment in these technologies is working. The literature suggests that the right measures sit one level below the technology, at the capabilities it strengthens. Marinagi et al. (2023) make this explicit by linking Industry 4.0 technologies not to resilience in the abstract but to specific key performance indicators that capture flexibility, visibility, collaboration, robustness, and information sharing. This matters because it offers a way to evaluate progress that does not depend on rare, catastrophic disruptions to reveal whether a chain is resilient. A firm can track whether its forecasts have become more accurate, whether its time to detect and respond to a problem has shortened, whether inventory is better matched to demand, and whether its partners share data more readily, and it can read improvements in these indicators as signs that resilience is being built. Smyth et al. (2024) reinforce the point by framing prescriptive analytics as a means of improving the quality and speed of decisions rather than as an end in itself, and Dubey et al. (2023) tie digital capability to resilience through measurable shifts in agility. Reading these studies together suggests a measurement logic that runs from technology, to the capabilities it enables, to the performance indicators that capture those capabilities, and finally to resilience and sustainability outcomes. Firms that measure only the first and last of these, the spending and the eventual disruption, will struggle to learn, while those that track the capabilities in between can steer their investments as they go. There is a further benefit to measuring at the level of capabilities. Disruptions large enough to test resilience are, by their nature, rare, so a firm that waits for one to judge whether its investments worked will learn slowly and at great cost. Capability indicators, by contrast, can be observed continuously in ordinary operations, which turns resilience from something that is only revealed in a crisis into something that can be managed day to day. This reframing aligns with the broader argument of the review, that resilience is built through capabilities rather than bought as a product, and it gives practitioners a concrete way to act on that insight.

Barriers to adoption

Several barriers continue to slow widespread implementation, and they deserve to be named individually because each calls for a different response. The first is cybersecurity and data privacy. As supply chains become more connected, the surface exposed to attack widens, and the sharing of sensitive operational data across partners raises questions of ownership and protection (Nozari et al., 2022). The second is interoperability with legacy systems, since many control systems were not designed to exchange data with modern AI tools and require substantial redesign or middleware before they can do so. The third is cost and organisational resistance. The investment in sensing, computing, and skilled people can be heavy, and it weighs most on smaller firms, some of which adopt technologies only once they have become mainstream and the competitive advantage has largely passed.

The fourth barrier is the digital skills gap, a human factor that recurs throughout the literature. Realising value from these technologies requires analytical and data skills that are in short supply, and closing the gap calls for continuous training and a shift towards a data-driven culture rather than a one-off investment (Shahzadi et al., 2024). The fifth is the limited interpretability of complex models. Decisions taken by opaque systems are difficult to trust and act upon in settings where safety and compliance matter, which has prompted a dedicated stream of work on explainability in supply chain risk management (Nimmy, Hussain, Chakrabortty, Hussain, & Saberi, 2022). A sixth consideration, easily overlooked, is the energy footprint of large-scale AI, which can offset some of the sustainability gains the technology is meant to deliver and which sits awkwardly with the environmental goals of resilient and sustainable operations. These barriers are not independent of one another. Cost constrains the investment in skills, weak skills make integration harder, poor integration limits the data available to models, and limited data deepens the interpretability problem, since models trained on thin data are both less accurate and harder to trust. Recognising these connections matters, because it implies that removing a single barrier in isolation may achieve little. The firms and policymakers most likely to make progress are those that address the barriers as a connected set, sequencing investment so that each removed obstacle clears the way for the next. Table 2 summarises these barriers alongside the directions the literature proposes for each.

Table 2. Key barriers to adoption and emerging directions.

Barrier	Description	Emerging direction
Cybersecurity and data privacy	Greater connectivity widens exposure across partners	Security standards, blockchain-based trust
Interoperability with legacy systems	Older control systems were not built for AI	Digital twins and middleware as bridges
Cost and organisational resistance	High investment burden, hardest for smaller firms	Shared infrastructure, phased roadmaps, incentives
Digital skills gap	Shortage of analytical and data skills in the workforce	Continuous training, data-driven culture
Model interpretability	Black-box models limit trust in critical decisions	Explainable AI, human-in-the-loop oversight
Energy footprint of AI	Large-scale computation consumes significant energy	Efficient models, green-AI principles, edge computing

Source: Authors, compiled from the reviewed literature.

An integrated reading

Pulling these strands together, the central argument of the review is that AI delivers the most value when it is integrated rather than deployed in pieces. The technologies form a layered system in which IoT senses, predictive analytics anticipates, digital twins simulate and coordinate, blockchain secures the shared data, and AI supplies the learning intelligence that binds the layers in pursuit of resilience and sustainability. This reading is consistent with the convergence perspective in the literature and helps explain why piecemeal, single-technology adoption so often disappoints (Culot et al., 2024). It also reframes the familiar tension between the strong claims of applied case studies and the tempered conclusions of systematic reviews. That tension is not a contradiction so much as

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue VI June 2026

a difference of vantage point: applied studies report what is possible under favourable conditions, while reviews report what has been achieved on average across many settings. Both are informative, and the gap between them marks the work still to be done. Crucially, the integrated view also keeps people in the picture. The strongest gains so far come not from removing human judgement but from supporting it, which is precisely the promise of the Industry 5.0 vision and a reminder that full autonomy remains some way off (Ivanov, 2023; Jackson, 2024). The label of the autonomous supply chain, then, is best read as a direction of travel rather than a present reality. Most organisations today operate somewhere along a spectrum that runs from manual, report-driven management at one end to fully self-steering operations at the other, and the practical question is not whether to leap to the far end but how to move one step further along it. The layered architecture set out above is useful precisely because it makes that next step visible. A firm can ask which layer is weakest in its own operations, the sensing, the analytics, the simulation, the execution, or the feedback, and invest there, rather than pursuing autonomy as an all-or-nothing goal.

Weighing the evidence: well-supported and tentative claims

A synthesis is only as useful as its willingness to separate what the evidence supports from what remains speculative. Several claims in this field can be regarded as well supported, because they are corroborated across studies of different kinds. That AI improves demand forecasting, that IoT increases visibility, that digital twins enable disruption simulation, and that these technologies strengthen resilience indirectly by building capabilities such as flexibility and visibility are findings that recur across empirical studies, systematic reviews, and applied cases (Douaioui et al., 2024; Marinagi et al., 2023; Dubey et al., 2023). These can be stated with reasonable confidence.

Other claims remain tentative, and the review flags them as such. The prospect of fully autonomous supply chains, the specific benefits of generative AI, and the scale of sustainability gains once AI's own energy costs are netted out are supported more by conceptual argument and early studies than by robust, replicated evidence (Jackson, 2024). The literature also contains a genuine tension. Applied case studies tend to report strong, sometimes striking, benefits, while systematic reviews reach more cautious conclusions and warn against inflated expectations (Culot et al., 2024). This review reads that tension not as a contradiction to be settled in favour of one side, but as a signal that the technologies work well under favourable conditions that are not yet the norm, and that the gap between the two literatures marks precisely where more rigorous, comparative, and longitudinal evidence is needed.

Directions for further research

Several directions follow from the synthesis. The field would benefit from moving past single-technology studies towards integrated architectures that measure the joint contribution of IoT, predictive analytics, digital twins, and blockchain, rather than treating each in isolation. The resilience and sustainability relationship deserves direct empirical study, including the energy and computing costs of AI that can offset its sustainability benefits. Work on explainable AI, federated learning, and blockchain-based governance offers promising routes through the problems of interpretability, privacy, and trust (Nimmy et al., 2022; Kouhizadeh et al., 2021). More evidence is needed from the processes that current research neglects, particularly sourcing and returns, and from sectors beyond manufacturing and food, since the value of these technologies clearly varies by context (Guo & Mantravadi, 2025; Hu et al., 2023). Finally, the rapid rise of generative AI calls for dedicated study of both its capabilities and its risks in supply chain and operations management, a frontier that is only beginning to be mapped (Jackson, 2024). Two further directions deserve mention. The first is methodological. Much of the strongest evidence comes from systematic and bibliometric reviews, which describe the shape of the literature, and from individual case studies, which describe what is possible in one setting. The field would benefit from more studies in between, such as multi-firm comparisons and longitudinal work that follows adoption over time, since these are the designs best suited to separating the effect of the technology from the effect of the firms that adopt it. The second is the human and ethical dimension. As decisions shift towards algorithms, questions of accountability, fairness, workforce impact, and the appropriate division of labour between people and machines move from the margins to the centre, and they will require engagement from disciplines beyond operations and information systems.

Generative AI deserves particular attention as a research priority, since its role in supply chain resilience is still largely unexplored. Several possibilities stand out. Generative models could support resilience by drafting and comparing recovery scenarios in natural language, by summarising fragmented risk information from documents and communications that structured systems miss, and by serving as an accessible interface through which managers interrogate a digital twin. At the same time, their tendency to produce fluent but sometimes incorrect outputs poses a real risk in decisions where accuracy is critical, which suggests that early applications should keep a human firmly in control and should be evaluated against clear measures of reliability. Rigorous, domain-specific studies are needed to establish where generative AI genuinely strengthens resilience and where it introduces new fragilities (Jackson, 2024).

CONCLUSION AND POLICY RECOMMENDATION

Conclusion

The integration of AI, IoT, digital twins, and predictive analytics offers a transformative pathway towards resilient and sustainable supply chain operations. By bridging the physical and digital worlds, these technologies allow organisations to move from reactive management to proactive steering, anticipating disruption rather than merely responding to it. This review has shown that their value is realised through integration into a coherent, layered architecture, that their contribution to resilience runs through underlying capabilities such as visibility, flexibility, and collaboration rather than through the technology alone, and that their benefits vary by sector and setting. It has also been candid about the limits of current knowledge, including the gap between the strong claims of applied studies and the more measured conclusions of systematic reviews, and the obstacles of cost, cybersecurity, skills, interoperability, and interpretability that continue to slow adoption. While full autonomy remains complex and some way off, the synergy between predictive intelligence and virtual simulation already offers a meaningful advantage within the human-centric vision of Industry 5.0. The broader message of the review is one of cautious optimism. The technologies are real, their benefits are documented, and the direction of travel is clear, but the gains are neither automatic nor evenly distributed. They accrue to organisations that build the data foundations, skills, and integrated architectures that the technologies require, and that keep human judgement at the centre of consequential decisions. For supply chains facing a future of recurring disruption and rising environmental expectations, this is an encouraging conclusion, because it places the outcome largely within the control of the firms and policymakers willing to do the work.

Recommendations for practitioners

- Treat AI and digital twins as core, end-to-end capabilities rather than isolated pilot projects, and invest in the data foundations and interoperability that let the technologies reinforce one another (Richey et al., 2023).
- Invest in talent acquisition and training to close the digital skills gap and build a data-driven culture, since the organisational and human conditions for adoption matter as much as the technology itself (Shahzadi et al., 2024).
- Prioritise data quality and standardised protocols to ensure interoperability across platforms, and match technology choices to the specific risks of the firm's own chains rather than adopting a fixed template (Guo & Mantravadi, 2025).
- Begin with the processes where the dominant difficulty is clearest, such as demand forecasting or traceability, and extend the architecture outward as data foundations and capabilities mature (Douaioui et al., 2024).

Policy recommendations

- Establish clear regulatory frameworks for responsible data handling and ethical AI use, including support for explainable AI in critical supply chain decisions (Nimmy et al., 2022).
- Provide financial incentives and collaborative ecosystems to help smaller firms adopt advanced technologies, reducing digital disparities across the network (Kouhizadeh et al., 2021).

- Develop national and international cybersecurity standards to safeguard critical supply chain infrastructure against evolving threats (Nozari et al., 2022).

- Embed sustainability criteria, including the energy footprint of AI, into technology adoption frameworks so that the pursuit of resilience does not come at an environmental cost (Ivanov, 2023).

LIMITATIONS

This review has the usual limitations of its design. It rests on English-language, peer-reviewed journal articles published within the last five years and on an interpretive synthesis, so its conclusions depend on the quality of the work it draws upon and may not capture relevant evidence published in other languages, formats, or earlier periods. As an integrative review rather than a formal meta-analysis, it does not claim exhaustive coverage, and it reports the findings of primary studies rather than generating new empirical data. Because it relies on secondary sources, the review guards against the bias of any single study by giving greatest weight to conclusions that are corroborated across different kinds of evidence, namely empirical studies, systematic reviews, and applied cases, so that the synthesis rests on convergent rather than isolated findings. This remains a form of triangulation across the literature rather than the primary, multi-source validation that future empirical work could provide. These limits notwithstanding, the paper offers a consolidated and honestly sourced account of a fast-moving field and a foundation for the more rigorous, more integrated, and more sustainability-aware research that the next phase of work demands.

ACKNOWLEDGEMENTS

The authors thank Universiti Teknologi Malaysia and Azman Hashim International Business School for the facilities and support provided for this work, and acknowledge the guidance of the course lecturer, Assoc. Prof. Dr. Normal Mat Jusoh, as well as the researchers whose published work was synthesised in this review.

REFERENCES

1. Aljohani, A. (2023). Predictive analytics and machine learning for real-time supply chain risk mitigation and agility. Sustainability, 15(20), 15088. https://doi.org/10.3390/su152015088
2. Babai, M. Z., Boylan, J. E., & Rostami-Tabar, B. (2022). Demand forecasting in supply chains: A review of aggregation and hierarchical approaches. International Journal of Production Research, 60(1), 324–348.
3. Burgos, D., & Ivanov, D. (2021). Food retail supply chain resilience and the COVID-19 pandemic: A digital twin-based impact analysis and improvement directions. Transportation Research Part E: Logistics and Transportation Review, 152, 102412. https://doi.org/10.1016/j.tre.2021.102412
4. Culot, G., Podrecca, M., & Nassimbeni, G. (2024). Artificial intelligence in supply chain management: A systematic literature review of empirical studies and research directions. Computers in Industry, 162, 104132. https://doi.org/10.1016/j.compind.2024.104132
5. Deiva Ganesh, A., & Kalpana, P. (2022). Future of artificial intelligence and its influence on supply chain risk management: A systematic review. Computers & Industrial Engineering, 169, 108206.
6. Douaioui, K., Oucheikh, R., Benmoussa, O., & Mabrouki, C. (2024). Machine learning and deep learning models for demand forecasting in supply chain management: A critical review. Applied System Innovation, 7(5), 93. https://doi.org/10.3390/asi7050093
7. Dubey, R., Bryde, D. J., Dwivedi, Y. K., Graham, G., & Foropon, C. (2022). Impact of artificial intelligence-driven big data analytics culture on agility and resilience in humanitarian supply chain: A practice-based view. International Journal of Production Economics, 250, 108618.
8. Dubey, R., Bryde, D. J., Dwivedi, Y. K., Graham, G., Foropon, C., & Papadopoulos, T. (2023). Dynamic digital capabilities and supply chain resilience: The role of government effectiveness. International Journal of Production Economics, 258, 108790.
9. El Baz, J., & Ruel, S. (2021). Can supply chain risk management practices mitigate the disruption impacts on supply chains' resilience and robustness? Evidence from an empirical survey in a COVID-19 outbreak era. International Journal of Production Economics, 233, 107972.

10. Guo, D., & Mantravadi, S. (2025). The role of digital twins in lean supply chain management: Review and research directions. International Journal of Production Research, 63(5), 1851–1872.
11. Hu, H., Xu, J., Liu, M., & Lim, M. K. (2023). Vaccine supply chain management: An intelligent system utilizing blockchain, IoT and machine learning. Journal of Business Research, 156, 113480. https://doi.org/10.1016/j.jbusres.2022.113480
12. Iftikhar, A., Ali, I., Arslan, A., & Tarba, S. (2024). Digital innovation, data analytics, and supply chain resiliency: A bibliometric-based systematic literature review. Annals of Operations Research, 333(2), 825–848.
13. Ivanov, D. (2023). The Industry 5.0 framework: Viability-based integration of the resilience, sustainability, and human-centricity perspectives. International Journal of Production Research, 61(5), 1683–1695.
14. Ivanov, D. (2024). Two views of supply chain resilience. International Journal of Production Research, 62(11), 4031–4045.
15. Ivanov, D., & Dolgui, A. (2021). A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. Production Planning & Control, 32(9), 775–788. https://doi.org/10.1080/09537287.2020.1768450
16. Jackson, I. (2024). Generative artificial intelligence in supply chain and operations management: A capability-based framework for analysis and implementation. International Journal of Production Research, 62, 6120–6145. https://doi.org/10.1080/00207543.2024.2309309
17. Kouhizadeh, M., Saberi, S., & Sarkis, J. (2021). Blockchain technology and the sustainable supply chain: Theoretically exploring adoption barriers. International Journal of Production Economics, 231, 107831.
18. Marinagi, C., Reklitis, P., Trivellas, P., & Sakas, D. (2023). The impact of Industry 4.0 technologies on key performance indicators for a resilient supply chain 4.0. Sustainability, 15(6), 5185. https://doi.org/10.3390/su15065185
19. Nayal, K., Raut, R. D., Queiroz, M. M., Yadav, V. S., & Narkhede, B. E. (2021). Are artificial intelligence and machine learning suitable to tackle the COVID-19 impacts? An agriculture supply chain perspective. The International Journal of Logistics Management, 34(2), 304–335.
20. Nimmy, S. F., Hussain, O. K., Chakrabortty, R. K., Hussain, F. K., & Saberi, M. (2022). Explainability in supply chain operational risk management: A systematic literature review. Knowledge-Based Systems, 235, 107587.
21. Nozari, H., Szmelter-Jarosz, A., & Ghahremani-Nahr, J. (2022). Analysis of the challenges of Artificial Intelligence of Things (AIoT) for the smart supply chain (case study: FMCG industries). Sensors, 22(8), 2931. https://doi.org/10.3390/s22082931
22. Pournader, M., Ghaderi, H., Hassanzadegan, A., & Fahimnia, B. (2021). Artificial intelligence applications in supply chain management. International Journal of Production Economics, 241, 108250. https://doi.org/10.1016/j.ijpe.2021.108250
23. Rahman, T., Paul, S. K., Shukla, N., Agarwal, R., & Taghikhah, F. (2022). Supply chain resilience initiatives and strategies: A systematic review. Computers & Industrial Engineering, 170, 108317. https://doi.org/10.1016/j.cie.2022.108317
24. Riad, M., Naimi, M., & Okar, C. (2024). Enhancing supply chain resilience through artificial intelligence: Developing a comprehensive conceptual framework for AI implementation and supply chain optimization. Logistics, 8(4), 111. https://doi.org/10.3390/logistics8040111
25. Riahi, Y., Saikouk, T., Gunasekaran, A., & Badraoui, I. (2021). Artificial intelligence applications in supply chain: A descriptive bibliometric analysis and future research directions. Expert Systems with Applications, 173, 114702. https://doi.org/10.1016/j.eswa.2021.114702
26. Richey, R. G., Chowdhury, S., Davis-Sramek, B., Giannakis, M., & Dwivedi, Y. K. (2023). Artificial intelligence in logistics and supply chain management: A primer and roadmap for research. Journal of Business Logistics, 44(4), 532–549. https://doi.org/10.1111/jbl.12364
27. Roman, E.-A., Stere, A.-S., Roşca, E., Radu, A.-V., Codroiu, D., & Anamaria, I. (2025). State of the art of digital twins in improving supply chain resilience. Logistics, 9(1), 22. https://doi.org/10.3390/logistics9010022
28. Sallam, K., Mohamed, M., & Wagdy Mohamed, A. (2023). Internet of Things (IoT) in supply chain management: Challenges, opportunities, and best practices. Sustainable Machine Intelligence Journal, 2(3), 1–32. https://doi.org/10.61185/SMIJ.2023.22103

29. Samuels, A. (2025). Examining the integration of artificial intelligence in supply chain management from Industry 4.0 to 6.0: A systematic literature review. Frontiers in Artificial Intelligence, 7, 1477044. https://doi.org/10.3389/frai.2024.1477044
30. Saurabh, S., & Dey, K. (2021). Blockchain technology adoption, architecture, and sustainable agri-food supply chains. Journal of Cleaner Production, 284, 124731. https://doi.org/10.1016/j.jclepro.2020.124731
31. Shahzadi, G., Jia, F., Chen, L., & John, A. (2024). AI adoption in supply chain management: A systematic literature review. Journal of Manufacturing Technology Management, 35(6), 1125–1150. https://doi.org/10.1108/JMTM-09-2023-0431
32. Smyth, C., Dennehy, D., Fosso Wamba, S., Scott, M., & Harfouche, A. (2024). Artificial intelligence and prescriptive analytics for supply chain resilience: A systematic literature review and research agenda. International Journal of Production Research, 62(23), 8537–8561. https://doi.org/10.1080/00207543.2024.2341415
33. Stewart, M., & Ivanov, D. (2022). Design redundancy in agile and resilient humanitarian supply chains. Annals of Operations Research, 319(1), 633–659.
34. Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P., & Fischl, M. (2021). Artificial intelligence in supply chain management: A systematic literature review. Journal of Business Research, 122, 502–517. https://doi.org/10.1016/j.jbusres.2020.09.009