

Revolutionizing Construction Supply Chain Management: Integrating Artificial Intelligence for Resilience, Efficiency, and Sustainability in the Digital Era

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Abstract

The construction industry remains hindered by fragmented, inefficient, and vulnerable supply chains that contribute to cost overruns, schedule delays, and environmental impacts. Although digitalisation offers potential solutions, the role of Artificial Intelligence (AI) in Construction Supply Chain Management (CSCM) has often been examined through isolated applications rather than through an integrated performance lens. This paper conducts a systematic literature review to synthesise how AI supports CSCM efficiency, resilience, and sustainability. Following PRISMA 2020 guidance, Scopus and Web of Science were searched for English-language studies and relevant scholarly sources published from 1994 to May 2025. From 1,452 records initially identified, 347 duplicates were removed, 1,105 records were screened, 140 full texts were assessed, and 28 sources were included in the qualitative synthesis. The review identifies three main application streams: machine-learning-based forecasting and optimisation for procurement, logistics, and equipment management; digital twins and predictive analytics for disruption anticipation and adaptive response; and AI-enabled waste minimisation, circular material flows, and carbon-aware supplier and logistics decisions. The synthesis shows that AI can create synergies among efficiency, resilience, and sustainability, but it can also generate trade-offs when single-objective optimisation dominates. The paper contributes an AI-Driven Cognitive CSCM Framework linking data infrastructure, AI analytics, application layers, and human-AI governance. The review further identifies data fragmentation, organisational resistance, interoperability limits, cybersecurity exposure, human-AI trust, and algorithmic ethics as priority barriers for future research and implementation.

Keywords: Artificial Intelligence, Construction Supply Chain Management (CSCM), Sustainability, Systematic Literature Review, Digital Twin.

1 Introduction

The construction industry serves as a fundamental engine for global economic and social development, yet it is paradoxically plagued by chronic issues of low productivity, significant cost overruns, and frequent schedule delays (Latif, 2023; Baarimah et al., 2026). For decades, seminal reports have highlighted the sector's fragmentation and adversarial nature as key impediments to performance improvement (Latham, 1994; Egan,

1998). At the heart of these systemic challenges lies the intricate and often chaotic nature of Construction Supply Chain Management (CSCM). Unlike the stable, repetitive supply chains of manufacturing, CSCM is characterised by its temporary, project-based structure, involving a disparate network of stakeholders, which often leads to information asymmetry, poor coordination, and reactive decision-making (Vrijhoef & Koskela, 2000).

These traditional inefficiencies are compounded by emerging pressures that require a paradigm shift. First, the increasing frequency of global disruptions, including pandemics and geopolitical conflicts, has exposed the vulnerability of linear, cost-optimised supply chains; resilience is therefore no longer optional but essential for operational continuity (Ivanov, 2020). Cybersecurity has also become a central dimension of modern resilience because supply-chain digitalisation creates new capabilities while introducing new threat vectors (Roman, 2025; Singh, 2024). Second, there is an urgent global mandate for sustainability. The construction industry is responsible for a substantial share of resource depletion, greenhouse gas emissions, and waste generation (UN Environment Programme, 2021), which has accelerated interest in circular economy principles and sustainable supply-chain practices (Benachio et al., 2020).

The need to pursue efficiency, resilience, and sustainability simultaneously represents a multidimensional challenge that traditional CSCM models are not adequately equipped to address. A promising response is the digital transformation of the sector under the Construction 4.0 paradigm (Al-Azazi et al., 2025; Kasim et al., 2025). At the centre of this transition is Artificial Intelligence (AI), a family of technologies capable of learning from data, identifying patterns, and supporting complex decisions (Russell & Norvig, 2010). AI subfields such as Machine Learning (ML), Digital Twins, and Computer Vision have the potential to transform CSCM from a reactive, experience-based practice into a more proactive and data-driven management system (Abioye et al., 2021; Pan & Zhang, 2021).

However, the growing interest in applying AI in construction has produced a fragmented body of research. Much of the reviewed literature emphasises individual applications or isolated performance outcomes rather than the combined effect of AI on the supply chain as an integrated system (Darko et al., 2020; Alawag et al., 2024). A knowledge gap therefore remains regarding how AI can simultaneously support efficiency, resilience, and sustainability in CSCM, and how these outcomes interact through synergies, trade-offs, and adoption barriers. This paper addresses that gap by conducting a systematic literature review and by proposing an integrated AI-Driven Cognitive CSCM Framework.

This study is guided by the following research questions:

- i. What are the primary applications of AI in enhancing the efficiency, resilience, and sustainability of CSCM?
- ii. What are the key synergies and trade-offs between these three performance pillars when mediated by AI?
- iii. What are the significant challenges and barriers, including human-AI interaction (Emmanuel, 2025) and ethical considerations (Uwakweh, 2025), to the widespread adoption of AI in CSCM?

The research aim is to develop a novel "AI-Driven Cognitive CSCM Framework" that provides an integrated model for harnessing AI to create intelligent, adaptive, and sustainable construction supply chains.

2 Literature Review

2.1 The Evolving Landscape of Construction Supply Chain Management (CSCM)

The management of supply chains in the construction industry is a uniquely complex endeavour, fundamentally distinct from the more predictable models found in manufacturing. Traditionally, CSCM has been defined by its project-specific, temporary, and fragmented nature, bringing together a diverse array of stakeholders—clients, contractors, consultants, and suppliers—for a limited duration (Vrijhoef & Koskela, 2000). This inherent fragmentation has been a persistent source of inefficiency, leading to challenges such as poor coordination, adversarial relationships, and a lack of transparency, as highlighted in foundational industry reports (Latham, 1994; Egan, 1998). The consequences manifest as the chronic delays and cost overruns that continue to afflict the sector (Latif, 2023).

In recent years, this already complex environment has been subject to two powerful forces, both of which are non-negotiable: the demand for resilience and the mandate for sustainability. This transition of resilience from a theoretical discussion topic to a strategic necessity is being driven by an increase in global disruptions, such as pandemics and geopolitical events, as well as the brittleness of traditional cost-oriented supply chains (Ivanov, 2020). At the same time, the increasing digitalisation of the sector poses enormous cybersecurity challenges that endanger the functioning of the entire supply chain and require stronger defences (Singh, 2024; Roman, 2025). At the same time, the focus on sustainability has gained significant momentum. The construction industry is one of the largest consumers of natural resources and the largest contributor to global carbon emissions (UN Environment Programme, 2021); hence, there is increasing pressure for more responsible practices. This has increased interest in the Circular Economy (CE), which departs from the linear ‘take-make-dispose’ model in favour of a closed-loop economy that eliminates waste and maximises material reuse (Benachio et al., 2020; Safran et al., 2025; Musarat et al., 2022). This view necessitates a total paradigm shift in the way we think about CSCM, from the selection and buying of materials to the disassembly and reclamation at the end of life. The intersection of these pressures has shifted the focus of contemporary CSCM from being concerned only with cost and time optimisation (efficiency) to operating within a complex three-dimensional space defined by the often-conflicting goals of efficiency, resilience, and sustainability. In turn, this simply implies a fundamental need to evolve our management and development paradigms into smarter, more adaptive, integrated, and synergistic processes.

2.2 Artificial Intelligence as a Transformative Enabler in CSCM

As CSCM becomes more complex and subject to greater pressure, there is a need to move away from the current reactive management philosophy towards a more intelligent, predictive, and adaptable approach. Among these, the various technologies encompassed by the term Artificial Intelligence (AI) hold perhaps the greatest potential to enable such a change (Abioye et al., 2021). AI is not one technology, but rather a field of computer science concerned with developing systems that perform tasks that ordinarily require human intelligence, such as learning, reasoning, solving problems, and understanding language (Russell & Norvig, 2010). In these terms, AI can potentially analyse big data, identify patterns that are not obvious to the naked eye, and automate complex decision-making, thus tackling fundamental inefficiencies and weaknesses inherent not only in CSCM but also in the overall Construction 4.0 paradigm (Al-Azazi et al., 2025).

Artificial intelligence is being applied to construction in a range of ways, drawing upon several important sub-fields to address various challenges. ML is a subset of AI that employs algorithms to analyse past data to make predictions or decisions based on data without being programmed to do so. In CSCM, this can be applied to predicting material demand, project delays, and site safety hazards (Adeloye et al., 2023). Computer Vision gives the system the ability to understand and interpret visual information in the world, allowing for uses such as automated progress tracking, quality control inspections, and site safety surveillance (Pan & Zhang, 2021). Another compelling concept is the Digital Twin, which refers to the dynamic virtual representation of a physical

asset or system. Digital twins enable simulations, what-if scenario planning, and supply chain optimisation, and can take advantage of real-time data from sensors (IoT) to improve resilience (Singh, 2024).

But the application of AI in construction is still young. Although many of the individual AI applications have proven to have great potential, the research is often disconnected and addresses only specific problem areas, rather than looking at the entirety of the integrated supply chain (Darko et al., 2020). To truly transform business with AI, we must move beyond point solutions to a framework and theory around how we use these technologies to build an orchestrated cognitive supply chain, one capable not only of performing tasks but also of sensing, learning, and adapting. Each of the next sections will break down the deployment of AI along the three key performance pillars of efficiency, resilience, and sustainability to lay the groundwork for an integrated framework.

2.3 AI Applications for Enhancing CSCM Efficiency

Efficiency remains the historical anchor of CSCM because construction projects are typically assessed through cost, time, quality, and resource-utilisation performance. In fragmented construction supply chains, efficiency losses arise from delayed material delivery, inaccurate demand forecasting, manual procurement processes, disconnected schedules, and limited visibility across contractors and suppliers (Vrijhoef & Koskela, 2000; Latif, 2023). AI is therefore positioned in the literature as a potential enabling mechanism for prediction, optimisation, and automation; however, these mechanisms need to be interpreted within the broader CSCM context rather than as isolated technical solutions (Abioye et al., 2021; Pan & Zhang, 2021).

Accordingly, this subsection provides conceptual background rather than detailed review findings. The specific AI-enabled efficiency applications identified through the reviewed sources are synthesised later in the Results section, where they are directly mapped to CSCM tasks, efficiency outcomes, and relevant references.

2.4 Fortifying CSCM Resilience through AI

Whereas efficiency has long shaped CSCM practice, resilience has become a strategic requirement because construction supply chains must prepare for, absorb, recover from, and adapt to disruptions (Ivanov, 2020). Traditional lean and single-sourcing strategies may reduce short-term costs, but they can also create brittle supply networks when materials, logistics routes, or suppliers fail. Within this background, resilience is not treated as an alternative to efficiency; rather, it is a complementary capability that determines whether projects can maintain continuity under uncertainty. AI, predictive analytics, and digital twins are relevant to resilience because they can improve visibility, scenario analysis, and response coordination across interdependent stakeholders (Singh, 2024; Alaghbari et al., 2026). At the literature-review level, these technologies establish the conceptual foundation for understanding how data-driven tools may support risk anticipation and adaptive decision-making. The specific resilience applications and evidence patterns identified from the selected sources are presented in the Results section. Digitalisation also expands the resilience agenda by introducing cybersecurity and system-integrity concerns. As BIM, IoT, enterprise systems, and cloud platforms become more interconnected, cyber incidents can disrupt procurement, design coordination, payment flows, and site operations (Roman, 2025). Consequently, resilience in AI-enabled CSCM includes both physical disruption management and protection of the digital systems on which supply-chain decisions increasingly depend.

2.5 Driving Sustainability in CSCM with AI

Sustainability has become a defining requirement for CSCM because construction supply chains influence material extraction, transportation emissions, waste generation, energy use, and end-of-life recovery (UN Environment Programme, 2021; Zada et al., 2026). Within this background, sustainability is not limited to environmental compliance; it includes decisions about procurement, logistics, material reuse, and circular economy pathways (Benachio et al., 2020). AI is relevant because it can support data-intensive assessment and

optimisation of these decisions, but the detailed application patterns are treated as review findings in the Results section.

The sustainability literature also emphasises the need to move from linear material flows toward circular and regenerative supply-chain models. Concepts such as material passports, supplier environmental performance, and carbon-aware logistics provide the conceptual basis for AI-enabled sustainability in CSCM (Abioye et al., 2021; Manucharyan, 2021). This framing reduces overlap with the Results section by reserving the detailed synthesis of waste minimisation, circular material matching, and carbon-footprint reduction for the thematic analysis.

3 Research Method

A Systematic Literature Review (SLR) was used to answer the research questions in a comprehensive, replicable, and transparent manner. The SLR approach is suitable for consolidating a dispersed body of knowledge and identifying what is known, what remains uncertain, and where future research is required (Tranfield et al., 2003). To strengthen reporting transparency, the review process followed the PRISMA 2020 guidance for systematic reviews (Page et al., 2021). The process was implemented in four stages: (1) identifying the research questions, (2) developing the search strategy, (3) applying study-selection criteria and screening the literature, and (4) extracting and synthesising the data.

3.1 Guiding Research Questions

The entire review process was guided by the research questions established in the introduction. These questions framed the search strategy and the subsequent thematic analysis to ensure the review remained focused on its core objectives:

- i. **RQ1:** What are the primary applications of Artificial Intelligence in enhancing the efficiency, resilience, and sustainability of Construction Supply Chain Management (CSCM)?
- ii. **RQ2:** What are the key synergies and trade-offs between these three performance pillars when mediated by AI?
- iii. **RQ3:** What are the significant challenges and barriers, including human-AI interaction and ethical considerations, to the widespread adoption of AI in CSCM?

3.2 Search Strategy and Information Sources

A comprehensive search strategy was designed to identify relevant literature on AI-enabled CSCM. The search was conducted in Scopus and Web of Science, which were selected because of their broad coverage of engineering, construction management, technology, and management literature. The search covered publications and relevant scholarly sources from 1994 to May 2025; this timeframe captures foundational CSCM contributions, systematic-review methodology sources, and recent AI, digital twin, cybersecurity, and sustainability studies. The search query was constructed using Boolean operators (AND/OR) to combine three conceptual blocks: (1) the construction context, (2) AI-related technologies, and (3) performance pillars. The search was performed in the Title, Abstract, and Keywords fields to maximise relevance while retaining sufficient recall. The final search string was structured as follows:

((("construction industry" OR "AEC industry" OR "construction supply chain") AND ("artificial intelligence" OR "machine learning" OR "digital twin") AND ("efficiency" OR "resilience" OR "sustainability" OR "risk" OR "waste reduction")))

3.3 Study Selection and Screening

The screening process followed a systematic, multi-stage procedure, which is visually summarised in the PRISMA flow diagram (**Figure 1**).

Inclusion criteria were: (i) direct relevance to CSCM or construction/AEC supply-chain processes; (ii) explicit discussion of AI, ML, digital twins, computer vision, BIM-enabled analytics, optimisation, or related digital technologies; (iii) connection to efficiency, resilience, sustainability, risk, waste, logistics, procurement, or supplier management; (iv) English language; and (v) peer-reviewed journal or conference papers, or authoritative foundational and methodological sources required to frame the review. Exclusion criteria were: (i) studies outside the construction/AEC context; (ii) records discussing digitalisation without a clear AI or supply-chain relevance; (iii) non-English records; (iv) duplicates or records for which the full text was not accessible; and (v) studies that did not provide sufficient methodological, conceptual, or empirical relevance to RQ1-RQ3.

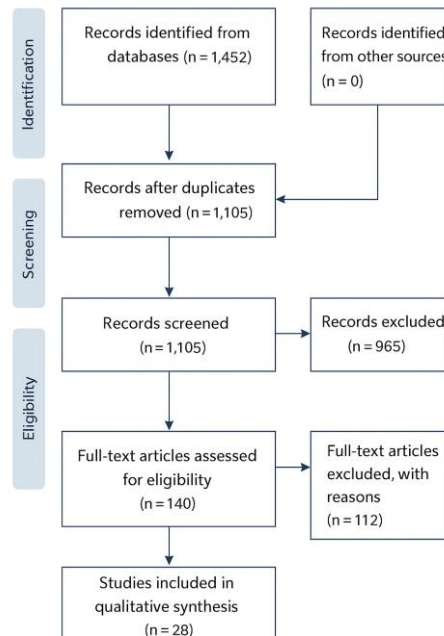


Figure 1. PRISMA 2020 Flow Diagram (Source: Adapted from Page et al., 2021)

Identification: The initial search yielded 1,452 records from the selected databases.

Screening (Phase 1): After automatic removal of 347 duplicates, the titles and abstracts of the remaining 1,105 records were independently screened by two researchers against the eligibility criteria. Disagreements were resolved through discussion and consensus to reduce selection bias and improve screening reliability.

Eligibility (Phase 2): The full texts of the remaining 140 records were assessed by the same two reviewers using the inclusion and exclusion criteria. Records were excluded when they did not directly address the intersection of AI, CSCM, and at least one of the three performance pillars, or when they lacked sufficient relevance to the research questions.

Inclusion: A final corpus of 28 sources was deemed suitable and included in the qualitative synthesis.

3.4 Data Extraction and Synthesis

A structured data extraction form was developed to systematically collect key information from each of the 28 included sources, including: (a) author(s) and year; (b) AI technique(s) or digital technology addressed; (c) application within CSCM; (d) performance pillar(s) addressed (efficiency, resilience, sustainability); (e) key findings or conceptual contribution; and (f) identified challenges and barriers.

For data synthesis, a thematic analysis was employed (Braun & Clarke, 2006). This involved identifying, analysing, and reporting recurring patterns (themes) across the literature. The analysis was structured around the three core pillars of this study, allowing for the mapping of AI applications to specific objectives and the identification of synergies, trade-offs, and overarching challenges, which are presented in the Results section.

4 Results and Analysis

This section presents the findings derived from the systematic literature review of 28 included sources. The analysis is organised to answer the research questions explicitly: Sections 4.2.1-4.2.3 address RQ1 by synthesising the primary AI applications across efficiency, resilience, and sustainability; Section 4.3 addresses RQ2 by analysing synergies and trade-offs among the three pillars and addresses RQ3 by summarising the main adoption barriers. This structure strengthens the link between the evidence base, the research questions, and the proposed framework.

4.1 Descriptive Analysis of Literature

The final corpus of 28 sources forms the evidence base for this review. These sources, published or cited between 1994 and 2025, reflect the evolution of CSCM from foundational discussions on fragmentation and procurement reform to recent work on AI, digital twins, cybersecurity, and sustainability. The selected literature is diverse, encompassing foundational reports and methodological sources as well as recent AI-oriented construction studies. A comprehensive overview of the selected sources, detailing their core focus, the performance pillar(s) addressed, and the methodology or source type employed, is presented in Table 1. This table provides a transparent map of the evidence base and clarifies how the reviewed and cited sources support the subsequent synthesis.

Table 1. Descriptive Summary of Selected Literature

Author(s) & Year	Core Focus	Performance Pillar(s) Addressed	Methodology
Latham, M. (1994)	Construction industry fragmentation and adversarial relationships.	Efficiency	Industry Review / Report
Egan, J. (1998)	Improving construction performance and efficiency.	Efficiency	Industry Review / Report
Vrijhoef, R., & Koskela, L. (2000)	Theoretical roles and philosophy of supply chain management in construction.	Efficiency	Conceptual Paper
Tranfield, D. et al. (2003)	Methodology for conducting systematic literature reviews in management.	(Methodology Paper)	Methodological Guidance
Braun, V., & Clarke, V. (2006)	Methodology for conducting thematic analysis in qualitative research.	(Methodology Paper)	Methodological Guidance
Russell, S. J., & Norvig, P. (2010)	Foundational principles and techniques of Artificial Intelligence.	(Foundational Text)	Textbook

UN Environment Programme (2021)	Global status of the buildings and construction sector regarding emissions.	Sustainability	Global Status Report
Benachio, J. A. et al. (2020)	Circular Economy principles and applications in the construction industry.	Sustainability	Systematic Literature Review
Ivanov, D. (2020)	Impact of epidemics on global supply chains and the need for resilience.	Resilience	Simulation-based Analysis
Zekhnini, K. et al. (2020)	Using BIM and predictive analytics for construction waste minimisation.	Efficiency, Sustainability	Case Study / Modelling
Darko, A. et al. (2020)	Review of the application of AI in the construction industry.	Efficiency, Sustainability	Literature Review
Manucharyan, H. (2021)	Multi-criteria decision making for supplier selection in supply chains.	Efficiency, Sustainability	Literature Review
Page, M. J. et al. (2021)	Updated PRISMA 2020 guidelines for reporting systematic reviews.	(Methodology Paper)	Methodological Guidance
Pan, Y., & Zhang, L. (2021)	Critical review of the roles of AI in construction management.	Efficiency	Critical Review
Abioye, S. O. et al. (2021)	Review of AI status, opportunities, and challenges in construction.	Efficiency, Resilience, Sustainability	Literature Review
Latif, M. (2023)	Key factors contributing to project delays in the construction industry.	Efficiency	Literature Review / Case Study
Adeloye, A. O. et al. (2023)	Review of AI applications in construction, focusing on observational studies.	Efficiency, Resilience	Literature Review
Alawag, A. M. et al. (2023)	Integrating Building Information Modelling (BIM) in heritage buildings.	Sustainability, Efficiency	Systematic Review
Bazel, M. A. et al. (2023)	Application of Blockchain technology in the construction industry.	Efficiency, Resilience	Bibliometric Analysis
Singh, A. (2024)	Role of Digital Twins in enhancing supply chain resilience.	Resilience	Conceptual Framework
Al-Azazi, S. A. et al. (2025)	Mitigating physical and cyber risks in smart construction infrastructure.	Resilience, Efficiency	Literature Review
Emmanuel, J. (2025)	Framework for Human-AI collaboration in project management.	Efficiency, Resilience	Conceptual Paper
Roman, D. (2025)	Cybersecurity issues in the construction industry's digital transformation.	Resilience	Analysis Paper
Savaş, M. A., & Tokyay, T. (2025)	Integrating BIM for enhanced energy performance and sustainability.	Efficiency, Sustainability	Review / Case Study
Uwakweh, B. O. (2025)	Ethical considerations and challenges of AI in supply chain management.	Sustainability, Resilience	Conceptual Paper
Elkington, J. (1999)	The "Triple Bottom Line" concept	Sustainability,	Foundational Work

	(Economic, Social, Environmental).	Efficiency	
Building... Author, 2017)	(No Review of BIM and its impact on building energy performance.	Efficiency, Sustainability	Literature Review
Alawag, A. M. et al. (2024)	TQM and IR 4.0 in sustainable industrialised building systems.	Efficiency, Sustainability	Framework Development

4.2 Thematic Analysis: AI Applications in CSCM

The thematic analysis identified AI applications aimed at enhancing CSCM performance and coded them against RQ1. The applications were categorised according to the three primary pillars of this study: efficiency, resilience, and sustainability. This coding enables the Results section to distinguish between background concepts and the specific findings generated from the reviewed sources.

4.2.1 AI Applications for Enhancing CSCM Efficiency

In response to RQ1, the review revealed that the most mature area of AI application in CSCM is operational efficiency. The primary focus is on leveraging AI to optimise cost, time, quality, procurement, logistics, and equipment utilisation. Key applications identified in the literature include predictive resource management, process automation, logistics optimisation, AI-enhanced BIM, and predictive maintenance. Table 2 maps these AI applications to their corresponding CSCM tasks and efficiency outcomes.

Table 2. Mapping of AI Applications to CSCM Efficiency Outcomes

AI Application / Technique	CSCM Task	Efficiency Outcome	Key References
Predictive Analytics (ML)	Demand & Material Forecasting	Reduced material waste, minimised inventory costs, and prevented shortages.	(Zekhnini et al., 2020)
Computer Vision	On-site Monitoring & Progress Control	Early detection of schedule deviations, automated quality inspection, and reduction in rework.	(Pan & Zhang, 2021)
AI-Powered Optimisation	Logistics & Route Planning	Minimised transportation costs and delivery times, reduced fuel consumption.	(Al-Azazi et al., 2025)
AI-Enhanced BIM	Automated Estimation (5D) & Cost Scheduling (4D)	Increased accuracy in budgeting and planning, reduction in manual errors.	(Savaş & Tokyay, 2025)
Predictive Maintenance	Equipment Management	Minimised unplanned downtime, extended equipment lifespan, and reduced repair costs.	(Abioye et al., 2021)

As shown in **Table 2**, Machine Learning models are widely proposed for forecasting, transforming procurement from a reactive to a data-driven process (Manucharyan, 2021). By analysing historical data, these models can anticipate needs with high precision, enabling Just-In-Time (JIT) material delivery and mitigating a primary cause of project delays (Zekhnini et al., 2020). Similarly, the use of Computer Vision on construction sites automates the arduous task of progress tracking, providing project managers with real-time, objective data that allows for swift corrective actions when projects deviate from the plan (Pan & Zhang, 2021).

4.2.2 AI Applications for Fortifying CSCM Resilience

With respect to RQ1, the selected literature also indicates a strong and growing focus on using AI to build resilient supply chains. Resilience in CSCM refers to the ability to anticipate, absorb, adapt to, and recover from

disruptive events (Ivanov, 2020). The findings show that AI contributes to resilience primarily through proactive risk management, adaptive response capabilities, digital twin-based scenario analysis, and enhanced cybersecurity. Proactive risk management is a dominant theme, where AI is used to shift from a reactive to a predictive stance. Machine Learning models are frequently cited for their ability to analyse diverse datasets—spanning supplier performance, geopolitical events, and climate data—to forecast potential disruptions (Al-Azazi et al., 2025). This foresight enables supply chain managers to implement mitigating strategies, such as qualifying alternative suppliers or increasing buffer stocks for high-risk components, long before a crisis materialises. The concept of adaptive response is significantly enabled by Digital Twin technology. The literature highlights that digital twins provide a simulated environment where the supply chain can be "stress-tested" against various disruptive scenarios (Singh, 2024). This allows for the identification of vulnerabilities and the formulation of data-driven contingency plans. By modelling the cascading effects of disruption, AI can recommend optimal recovery pathways in real-time, significantly improving the speed and effectiveness of the response.

Finally, with the increasing reliance on interconnected digital platforms like BIM and IoT, cybersecurity has emerged as a critical pillar of supply chain resilience. The literature points to AI's dual role in this area. AI-driven security systems are essential for detecting and neutralising cyber threats in real-time. However, these systems also highlight the need for robust governance to protect the integrity of the AI models themselves against adversarial attacks, which could cripple the supply chain (Roman, 2025). The relationship between these AI-driven resilience strategies is illustrated conceptually in **Figure 2**.

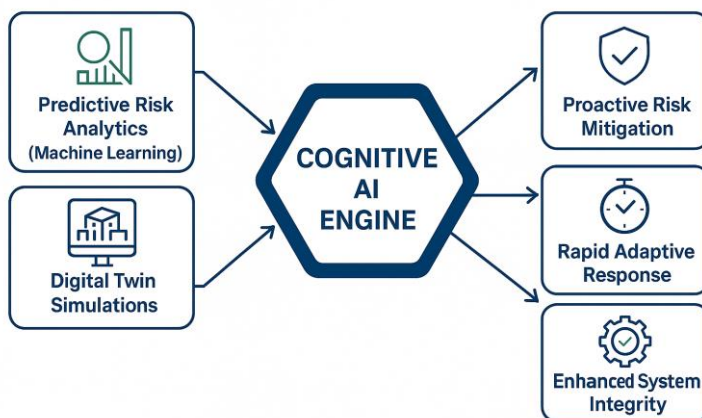


Figure 2. Conceptual Model of AI-Driven Resilience in CSCM (Source: The Authors)

4.2.3 AI Applications for Driving CSCM Sustainability

For RQ1, the analysis further confirms a strong thematic focus on the role of AI in addressing the environmental footprint of construction supply chains. Sustainability within CSCM is primarily framed around waste minimisation, circular economy implementation, and the reduction of energy consumption and carbon emissions (UN Environment Programme, 2021). The findings indicate that AI is a critical enabler for each objective. In waste management, the combination of AI and BIM can support design decisions that reduce material offcuts and waste volumes (Savaş & Tokyay, 2025), while ML models can forecast waste generation and support proactive waste-management planning (Zekhnini et al., 2020). Furthermore, AI is regarded as a prominent enabling technology for implementing the Circular Economy (CE). CE aims to shift from a linear take-make-dispose model to a regenerative model in which materials remain in use for as long as possible (Benachio et al., 2020). A recurring idea in the reviewed literature is the use of digital material passports that record material composition, lifecycle history, and deconstruction potential. Such information allows AI systems to match end-of-life materials from one project with the requirements of new projects, thereby

supporting secondary-material markets and reducing virgin resource consumption (Abioye et al., 2021). Finally, the reviewed literature shows that AI can contribute to carbon-footprint reduction across the supply chain. AI logistics platforms can improve routes, vehicle loads, and delivery schedules to reduce fuel consumption and associated greenhouse gas emissions (Al-Azazi et al., 2025). In procurement, AI-enhanced multi-criteria decision-making models can help select suppliers using cost, delivery performance, and environmental indicators, embedding sustainability within supply-chain decision-making rather than treating it as a separate compliance activity (Manucharyan, 2021).

4.3 Synergies, Trade-offs, and Overarching Challenges

This subsection answers RQ2 by showing that AI does not affect efficiency, resilience, and sustainability in isolation. The reviewed literature reveals strong synergies, potential trade-offs, and a set of cross-cutting challenges that must be addressed together. AI can produce synergies when an application targeted at one pillar also improves another. For example, AI-based logistics optimisation improves efficiency through lower transport cost and improves sustainability through reduced fuel use and carbon emissions (Al-Azazi et al., 2025). Similarly, AI-supported waste reduction improves sustainability while also lowering material costs (Zekhnini et al., 2020), and predictive maintenance improves efficiency by reducing downtime while strengthening resilience by preventing critical equipment failures (Abioye et al., 2021). Conversely, the reviewed literature points to trade-offs that require careful managerial judgement. A typical example is the tension between lean efficiency and resilience: an AI model optimised only for cost may recommend single sourcing, which can reduce procurement cost but increase vulnerability to supplier disruption (Ivanov, 2020). Similarly, the cybersecurity protections needed for a resilient digital supply chain can create substantial implementation and maintenance costs, creating a short-term trade-off with efficiency objectives (Roman, 2025). The complex interactions and the dual positive and negative relationships are summarised in Table 3. In response to RQ3, the key adoption barriers identified across the reviewed sources can be summarised in three clusters. First, data fragmentation and interoperability limitations restrict the ability of AI systems to integrate BIM, IoT, ERP, procurement, logistics, and supplier information into a reliable data foundation. Second, organisational resistance, limited digital skills, unclear governance, and cost concerns slow implementation, especially where firms lack a mature data-driven culture. Third, ethical and trust-related concerns, including algorithmic bias, transparency, accountability, privacy, and cybersecurity exposure, require human-AI governance mechanisms before AI recommendations can be adopted confidently in CSCM (Abioye et al., 2021; Emmanuel, 2025; Roman, 2025; Uwakweh, 2025; Alawag, 2026).

Table 3. Synergies and Trade-offs between CSCM Performance Pillars Mediated by AI

Interaction	Synergy (Positive Reinforcement)	Trade-off (Potential Conflict)	Key References
Efficiency ↔ Resilience	Predictive maintenance (AI) reduces downtime (efficiency) and prevents critical failures (resilience).	Redundant supplier networks (resilience) increase procurement and coordination costs (efficiency).	(Abioye et al., 2021; Ivanov, 2020)
Efficiency ↔ Sustainability	Logistics optimisation (AI) reduces fuel costs (efficiency) and carbon emissions (sustainability).	Using premium sustainable materials (sustainability) may increase initial project costs (efficiency).	(Al-Azazi et al., 2025; Manucharyan, 2021)
Resilience ↔ Sustainability	Diversified local sourcing (resilience) reduces long-haul transportation emissions (sustainability).	Maintaining high buffer stocks for resilience may lead to increased warehousing energy use and potential material obsolescence/waste (sustainability).	(Benachio et al., 2020)

This pattern of interactions suggests that optimising for a single pillar in isolation is an incomplete strategy. A holistic approach is required, as conceptually illustrated in Figure 3. The model depicts efficiency, resilience,

and sustainability as interconnected vertices of a performance triangle. AI acts as the central cognitive engine that processes data and provides insights, enabling managers to navigate trade-offs, maximise synergies, and pursue a balanced performance position aligned with the multidimensional objectives of modern CSCM.

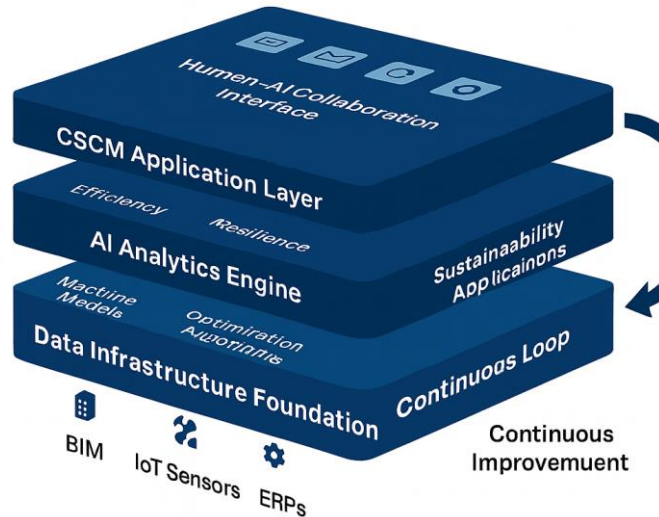


Figure 3. The AI-Driven Cognitive CSCM Framework (Source: The Authors)

4.4 AI-Driven Cognitive CSCM Framework

Based on the synthesis of the reviewed literature and the identified gaps, this paper proposes a conceptual model: the AI-Driven Cognitive CSCM Framework. The primary objective of this framework is to provide a holistic and strategic model for integrating AI into construction supply chains. It moves beyond isolated applications to create an intelligent, adaptive ecosystem capable of concurrently optimising efficiency, resilience, and sustainability. The framework is structured in four interconnected layers, as illustrated in Figure 3.

4.5 Layer 1: The Data Infrastructure Foundation

The foundation of the cognitive framework is a robust and integrated data infrastructure. This layer addresses the critical data-related challenges identified in the literature (Abioye et al., 2021). Its function is to aggregate, standardise, and secure data from a multitude of sources across the supply chain, including:

- i. **Building Information Models (BIM):** Providing detailed design, material, and geometric data.
- ii. **Internet of Things (IoT) Sensors:** Capturing real-time data from the construction site, warehouses, and logistics (e.g., equipment status, material location, environmental conditions).
- iii. **Enterprise Resource Planning (ERP) Systems:** Supplying data on procurement, supplier performance, and project financials.
- iv. **External Data Sources:** Incorporating data on weather forecasts, geopolitical risk, and market trends. A key component of this layer is a **Data Governance Protocol** that ensures data quality, interoperability, and cybersecurity (Roman, 2025), creating a "single source of truth" for the AI engine.

4.6 Layer 2: The AI Analytics Engine

This is the cognitive core of the framework, where raw data is transformed into actionable intelligence. This engine houses a suite of coordinated AI models and technologies:

- i. **Machine Learning Models:** For predictive tasks such as demand forecasting, delay prediction, waste generation forecasting, and risk identification.
- ii. **Optimisation Algorithms:** For prescriptive tasks like logistics route optimisation, resource scheduling, and procurement strategy selection.
- iii. **Digital Twin Simulators:** For what-if scenario analysis and stress-testing the supply chain's resilience against potential disruptions (Singh, 2024). This engine operates continuously, learning from new data to refine its models and improve the accuracy of its predictions and recommendations over time.

4.7 Layer 3: The CSCM Application Layer

This layer is where the insights from the AI Engine are operationalised. It directly maps AI capabilities to the three core performance pillars:

- i. **Efficiency Applications:** Automated cost estimation and control, dynamic scheduling adjustments, JIT material delivery coordination, and optimised equipment allocation.
- ii. **Resilience Applications:** Real-time risk alerts, automated contingency plan activation, and dynamic supplier diversification recommendations.
- iii. **Sustainability Applications:** Automated tracking of the carbon footprint, circular economy material matching (connecting waste streams to material needs), and optimisation of on-site energy consumption.

4.8 Layer 4: The Human-AI Collaboration Interface

- i. This top layer addresses the critical human and ethical dimensions of AI adoption. It is designed not to replace human managers but to augment their capabilities. Key features include:
- ii. **Integrated Dashboards:** Providing a holistic, real-time view of the supply chain's performance across all three pillars.
- iii. **Explainable AI (XAI) Tools:** Translating the "black box" decisions of AI models into understandable and justifiable reasoning, thereby building trust and facilitating informed human oversight (Emmanuel, 2025).
- iv. **Ethical Governance Module:** A system of checks and balances to monitor algorithmic bias and ensure that AI-driven recommendations align with the project's ethical and social responsibilities (Uwakweh, 2025). All four layers operate within a constant feedback loop. The supply chain provides data inputs to the AI engine, the engine produces insights deployed through the application layer, and human managers make strategic decisions through the collaboration interface. The results of those decisions create new data that continuously improves and adapts the system.

5 Discussion

This discussion interprets the review findings in relation to RQ1-RQ3 and explains how they support the proposed AI-Driven Cognitive CSCM Framework. For RQ1, the evidence shows that AI applications are most mature in efficiency-oriented tasks, particularly predictive resource management, logistics optimisation, process automation, and BIM-enabled planning. Resilience-oriented applications are expanding through predictive risk analytics, digital twins, cybersecurity monitoring, and adaptive response. Sustainability-oriented applications concentrate on waste minimisation, circular-economy material flows, energy optimisation, and carbon-aware supplier and logistics decisions. These findings justify the need for an integrated CSCM framework rather than a list of independent AI tools (Savaş & Tokyay, 2025; Zekhnini et al., 2020; Singh, 2024; Benachio et al., 2020; Al-Azazi et al., 2026).

For RQ2, the synergy and trade-off analysis summarised in Table 3 indicates that single-pillar optimisation is insufficient. Optimising only for cost efficiency can undermine resilience by encouraging vulnerable single-sourcing strategies (Ivanov, 2020), while stronger cybersecurity and redundancy can improve resilience but increase short-term costs (Roman, 2025). For RQ3, the review confirms three main barrier groups: data fragmentation and interoperability limitations; organisational resistance, skills gaps, and implementation-cost concerns; and ethical, transparency, accountability, privacy, and cybersecurity concerns. The layered architecture of the proposed framework addresses these barriers by placing data governance in the infrastructure layer and human-AI oversight in the collaboration interface (Abioye et al., 2021; Emmanuel, 2025; Uwakweh, 2025).

5.1 Theoretical Implications

This research makes several contributions to the existing body of knowledge. First, it extends the theory of CSCM by systematically integrating the three, often separately discussed, performance pillars of efficiency, resilience, and sustainability into a unified conceptual model. It argues that in the contemporary construction environment, these pillars are no longer optional but are deeply intertwined components of strategic supply chain management. Second, it contributes to the AI in Construction literature by moving beyond a narrow, tool-focused perspective. Instead of merely cataloguing applications, the proposed cognitive framework offers a strategic, top-down architecture that aligns AI capabilities with the overarching strategic goals of the construction firm. By doing so, it helps bridge the gap between the technical potential of AI and the strategic necessities of modern CSCM.

5.2 Managerial Implications

The findings and the proposed framework offer several actionable insights for project managers and decision-makers in the construction industry. The four-layered framework can be used as a strategic roadmap for a phased and structured adoption of AI, beginning with the establishment of a robust data infrastructure (Layer 1). It encourages managers to adopt a "balanced scorecard" approach to evaluating supply chain performance, where resilience and sustainability metrics are given equal weight alongside traditional efficiency metrics. Furthermore, it highlights the critical need for firms to invest in upskilling their workforce, fostering a culture of data-driven decision-making, and championing Human-in-the-Loop systems (Layer 4) that augment, rather than replace, human expertise, thereby building trust and ensuring effective implementation.

5.3 Limitations and Future Research

The authors acknowledge the limitations of this study. As a systematic literature review, the proposed framework is conceptual in nature and requires empirical validation through real-world case studies to test its applicability and effectiveness. While a comprehensive search strategy was employed, the review was limited to peer-reviewed articles in specific databases, and it is possible that some relevant insights from industry reports or conference proceedings were not captured.

This review opens several avenues for future research. The immediate priority is the empirical validation of the proposed framework. Future studies could apply the framework in a case study setting to measure its impact on a live construction project. Further research is also needed to develop specific, quantifiable metrics to help managers identify and maintain the optimal balance between efficiency, resilience, and sustainability. Finally, the Human-AI Collaboration Interface (Layer 4) and its ethical governance module represent a rich area for future exploration, requiring interdisciplinary research that combines computer science, project management, and organisational psychology.

6 Conclusion

This paper addressed the challenge of improving efficiency, resilience, and sustainability simultaneously in Construction Supply Chain Management (CSCM). Through a systematic literature review, the study synthesised AI applications across these three performance pillars and identified the lack of a consolidated model for integrating them. The main findings show that AI can enhance individual performance pillars, but its most important contribution lies in helping managers understand and manage the synergies and trade-offs among those pillars.

To address the identified gaps, the main contribution of this paper is the proposed AI-Driven Cognitive CSCM Framework. This four-layered model provides a strategic structure for developing data infrastructure, AI analytics capabilities, CSCM applications, and a human-centred ethical governance interface. The framework shifts AI adoption from isolated tools toward an integrated approach for building efficient, resilient, and sustainable construction supply chains. Ultimately, successful AI implementation in CSCM represents a transition from traditional reactive management to cognitive and proactive management. This framework provides a starting point for future empirical research and practical implementation in this important area.

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Declaration of Conflicting Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author Contribution

All authors contributed to the conception and design of the review, literature screening and synthesis, interpretation of the findings, and preparation and critical revision of the manuscript. All authors reviewed and approved the final version of the manuscript for publication.

Declaration of Generative Ai in The Writing Process

During the preparation of this work, the authors used OpenAI ChatGPT to improve readability, language quality, and copy-editing consistency. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Data Availability/Supplementary Materials

No new primary datasets were generated in this study. All information analysed in this systematic literature review is derived from the published sources cited in the article.

Ethics Statement

The authors declare that this research did not involve human participants or animal subjects; therefore, ethics committee approval and informed consent were not required.

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