

Review

Artificial Intelligence in Construction Supply Chains: A Scientometric Review and Future Research Agenda

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Abstract

Despite growing interest in artificial intelligence (AI) applications in the construction industry, the literature still lacks a consolidated understanding of how AI functions across the full spectrum of construction supply chain processes. Existing studies are dispersed across different technologies, project stages, and application contexts, making it difficult to identify the intellectual structure of this field, the main areas of AI application, and the barriers that continue to constrain practical implementation. To address this gap, this study conducts a systematic review of AI applications in construction supply chains by combining scientometric analysis with qualitative content synthesis. A total of 212 journal articles retrieved from Scopus were analyzed using VOSviewer-based scientometric analysis and qualitative content synthesis. The scientometric analysis maps annual publication trends, keyword co-occurrence patterns, co-cited sources, influential documents, and collaboration networks. The qualitative synthesis further examines how AI supports construction supply chain management across three broad themes: procurement and production optimization, logistics and material management, and collaborative decision-making for resilience and sustainability. The findings show that AI has been primarily applied to demand forecasting, resource optimization, logistics coordination, contract and document processing, computer vision-based monitoring, and multi-agent decision support. However, its practical diffusion remains constrained by fragmented and low-quality data, limited empirical validation, high implementation costs, algorithmic opacity, cybersecurity risks, and unresolved governance and liability issues. Based on these findings, this study proposes a data-centric and phased research agenda that emphasizes benchmark datasets, human–AI collaboration, lifecycle economic evaluation, explainable AI, and multi-stakeholder governance. The study contributes to the literature by integrating fragmented AI-related research into a structured knowledge map and by clarifying future pathways for developing intelligent, transparent, and resilient construction supply chains.



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1. Introduction

The construction supply chain is a decentralized, complex system. It comprises numerous stakeholders, activities, information flows, and resources essential for project delivery [1]. Historically, the construction industry has grappled with supply chain inefficiencies. These have led to persistent challenges, including delayed payments, a lack of

transparency, and contractual disputes [2,3]. Theoretically, AI offers a promising solution for supply chain optimization. It enables advanced data processing, pattern recognition, and adaptive learning [4]. Nevertheless, the application of AI within construction supply chains remains at an early stage. Further empirical investigation is needed to better understand its practical value and implementation conditions.

Rapid technological evolution has enabled sectors such as finance and logistics to adopt AI for prediction, optimization, automation, and risk control. In finance, AI and machine learning support fraud detection, credit and risk assessment, and algorithmic trading [5,6], while logistics applications include routing optimization, inventory management, and demand forecasting [7,8]. These applications demonstrate AI's value in data-intensive and uncertain environments involving interdependent decisions. Construction supply chains share these characteristics but face additional complexity from project-based production, fragmented organizational structures, temporary inter-firm collaboration, and site-specific resource flows. Therefore, lessons from other sectors must be adapted to the distinctive institutional and operational characteristics of construction supply chains. Furthermore, various industries are exploring the synergies between AI and other cutting-edge technologies, such as building information modelling (BIM), the internet of things (IoT), and blockchain [9–11]. In particular, the convergence of AI and blockchain can support predictive maintenance, process optimization, and supply chain visibility [12]. Although construction has historically lagged in digital technology adoption, recent evidence shows growing professional interest [13] and investment [14] in AI-enabled applications, including project analytics, planning, procurement, safety monitoring, and decision support.

The importance of supply chain optimization for project performance metrics, such as schedule attainment, cost control, and conflict management, is well-established. Materials remain one of the largest cost components in construction projects [15,16], and recent supply chain disruptions, logistics delays, material shortages, and price volatility have further intensified the risk of cost overruns and schedule delays in construction delivery [17]. AI offers significant potential to mitigate these persistent inefficiencies. Traditional construction procurement processes rely heavily on human experience and involve numerous intermediaries, which not only increase management costs but also exacerbate information asymmetry and the risk of system abuse. By deploying machine learning algorithms, firms can conduct granular analyses of historical data to predict material demand fluctuations and potential supply chain disruptions, thereby supporting a transition from reactive to proactive risk management [18]. Furthermore, natural language processing enables automated review of procurement contracts to identify high-risk clauses and enhance contract governance, thereby reducing the potential for disputes [19]. Additionally, intelligent systems based on reinforcement learning and computer vision enable the dynamic optimization of logistics routes and real-time monitoring of on-site execution [20]. This data-driven decision-making model minimizes human error and enhances the agility, transparency, and collaborative efficiency of the supply chain network by providing stakeholders with actionable, timely insights.

Despite the growing body of research on AI applications in the construction industry, current knowledge about AI-enabled construction supply chains remains fragmented. Existing studies have examined AI for specific construction tasks, such as cost prediction, schedule optimization, material monitoring, logistics planning, and risk assessment. Other studies have focused on the integration of individual digital technologies, including BIM, blockchain, IoT, digital twins, and automation systems. However, relatively limited attention has been paid to AI-enabled construction supply chains as an integrated socio-technical system involving procurement, production, logistics, material management, organizational collaboration, sustainability, resilience, and decision support. As a result, it remains unclear

how this research field has evolved, what application scenarios have received the greatest attention, what barriers constrain practical implementation, and what research directions should be prioritized to support future development.

To address these gaps, this study aims to provide a systematic understanding of how AI has been investigated and applied in construction supply chain research. Recent reviews have advanced knowledge of AI and digital technologies in construction. Sholeh et al. [4] provided a broad overview of AI applications, while Shishehgharkhaneh et al. [18] examined construction supply chain risk management. However, these studies do not explain how AI functions across construction supply chain processes or connect bibliometric knowledge structures with application domains, implementation barriers, and technology-integration pathways. This study therefore conceptualizes AI-enabled construction supply chains as an integrated socio-technical system involving procurement, production, logistics, material management, organizational collaboration, sustainability, resilience, and decision support. By combining scientometric analysis with qualitative content synthesis, it examines publication trends, knowledge structures, influential sources, collaboration patterns, application domains, implementation barriers, digital technology integration pathways, and future research directions. Specifically, this study addresses the following research questions:

RQ1. *How has research on AI-enabled construction supply chains evolved in terms of publication trends, intellectual structures, influential sources, and collaboration networks?*

RQ2. *How has AI been applied across construction supply chain processes, and what technological integration pathways and implementation barriers are reported in the literature?*

RQ3. *What future research directions are needed to support the development of intelligent, resilient, transparent, and sustainable construction supply chains?*

This study makes three contributions. First, it focuses specifically on AI-enabled construction supply chains and maps the intellectual structure of the field using 212 journal articles. By analyzing publication trends, keyword co-occurrence, co-cited sources, influential documents, and collaboration networks, it shows how research has evolved from isolated algorithmic applications toward more integrated, cross-organizational, and sustainability-oriented themes. Second, while existing reviews have mainly examined AI applications at the general construction-industry level or have focused on specific topics such as supply chain risk management, this study develops a process-oriented synthesis of AI applications across procurement, prefabricated production, logistics, material and inventory management, organizational collaboration, risk and resilience management, sustainability, and decision support. It clarifies where AI has been applied and how different AI techniques support prediction, optimization, monitoring, coordination, and governance across construction supply chains. Third, this study identifies key implementation barriers and proposes a phased research agenda covering benchmark datasets, data interoperability, lifecycle economic evaluation, explainable AI, human–AI collaboration, cybersecurity, liability allocation, and multi-stakeholder governance. This phased research agenda provides a supply-chain-specific pathway for moving from fragmented AI experimentation toward intelligent, transparent, and resilient construction supply chain management.

2. Research Methodology

This study employs a systematic literature review methodology combined with scientometric network analysis and qualitative content synthesis. The scientometric analysis is used to examine publication trends, keyword co-occurrence patterns, co-cited sources, influential documents, and collaboration networks, while the qualitative content synthesis is used to synthesize AI application scenarios, implementation barriers, technology integration pathways, and future research directions in construction supply chains. This combined

analytical design offers both a quantitative overview of research trends and a qualitative synthesis of thematic insights, thereby improving the transparency and interpretability of the review findings.

2.1. Identification and Screening of Publications

Scopus was selected because of its broad coverage of peer-reviewed literature in engineering, architecture, computer science, and management, as well as its structured bibliographic metadata suitable for scientometric analysis [1]. The search was conducted in April 2026 using titles, abstracts, and keywords, covering all eligible records indexed in Scopus up to that date. The search string combined AI-related terms with construction supply chain-related terms and procurement-related expressions.

The search string was developed iteratively. Initial keywords were derived from Shishehgarhaneh et al. [18] and Sholeh et al. [4], then expanded through pilot searches and reviews of highly relevant articles. Alternative term combinations were tested to balance recall and relevance. Although “generative AI,” “large language models,” “LLMs,” “GPT-based systems,” and “foundation models” were not standalone search terms, relevant studies were included when retrieved through broader terms such as artificial intelligence, natural language processing, expert systems, and optimization.

The initial search yielded 3840 records. After limiting the results to English-language, peer-reviewed journal articles in relevant subject areas and removing duplicates and incomplete records, 1144 publications remained. Abstract and full-text screening then excluded studies with only superficial AI relevance, non-construction supply chain contexts, or no clear supply chain-related process, resulting in a final sample of 212 journal articles for scientometric analysis and qualitative content synthesis. The inclusion and exclusion criteria are summarized in Table 1, while Figure 1 presents the PRISMA-style screening process.

Table 1. Inclusion and exclusion criteria for article selection.

Criterion	Inclusion Criteria	Exclusion Criteria
Document type	Peer-reviewed journal articles	Conference papers, book chapters, editorials, notes, reviews without empirical or conceptual relevance, and non-peer-reviewed materials
Language	Articles written in English	Articles written in languages other than English
Subject area	Engineering, architecture, computer science, management, and related construction/project management fields	Agriculture, food logistics, healthcare supply chains, manufacturing supply chains, or other non-construction domains
AI relevance	Articles that examine AI, machine learning, deep learning, computer vision, natural language processing, intelligent optimization, multi-agent systems, or related AI-enabled methods	Articles that only mention AI as background without substantive analysis or application
Construction supply chain relevance	Articles addressing procurement, supplier selection, logistics, prefabricated production, material and inventory management, construction supply chain coordination, risk/resilience, sustainability, or decision support	Articles focusing on isolated construction tasks without a supply chain connection, such as purely structural analysis or equipment-level automation
Data availability	Articles with sufficient bibliographic metadata for scientometric analysis and sufficient content for qualitative synthesis	Records with incomplete metadata, inaccessible full text, or insufficient information for coding

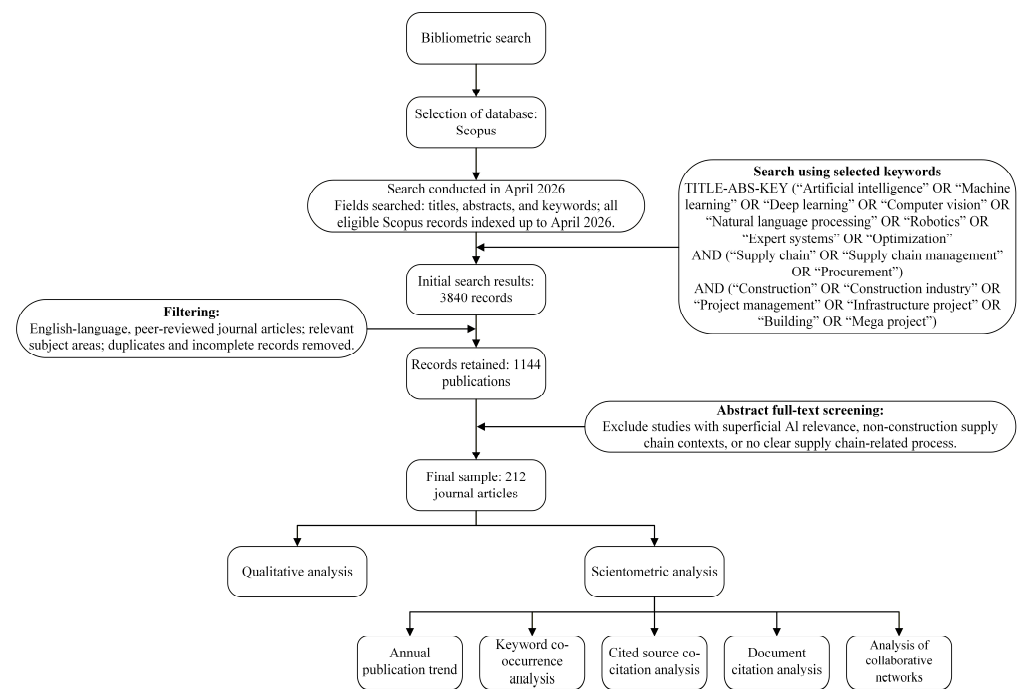


Figure 1. Research methodology flowchart.

2.2. Data Analysis

2.2.1. Scientometric Analysis Methods

This study used VOSviewer (version 1.6.20) for scientometric network analysis in accordance with Van Eck and Waltman [21]. The software was selected for its ability to generate, visualize, and explore complex bibliometric networks [1], consistent with Chen’s [22] criteria for science-mapping tools. Co-authorship, co-occurrence, and co-citation analyses were conducted to map research networks, knowledge structures, and emerging themes. Keyword occurrence frequency and total link strength were used to assess thematic prominence and relationships, following established construction management studies [1,23].

Analytical parameters were selected iteratively to balance network inclusiveness and visual interpretability. Relatively low thresholds were used because AI-enabled construction supply chain research remains emerging and fragmented, and higher thresholds could exclude recent or specialized topics. The full-counting method was adopted to give equal weight to each occurrence or relationship and capture the absolute visibility and connectivity of keywords, sources, documents, authors, and countries. The thresholds and retained items for each network are reported in the corresponding results subsections.

2.2.2. Qualitative Content Synthesis Analysis Methods

To complement the scientometric analysis, a qualitative content synthesis was conducted to examine AI applications, implementation barriers, digital technology integration pathways, and future research directions in construction supply chains.

The coding process involved three stages. First, an initial framework was developed from the research questions and a preliminary review of representative articles. It covered four dimensions: AI application scenarios, implementation barriers, integration pathways with other digital technologies, and research gaps and future directions. Second, two authors independently coded a pilot subset and refined the categories to improve clarity and consistency. Third, the finalized framework was applied to all 212 articles.

For each article, the coding recorded the research focus, construction supply chain process, AI technique, data source, application context, reported benefits, implementation challenges, and future research implications. Articles could be assigned to multiple cate-

gories. Disagreements were resolved through discussion, with a third author consulted when necessary. Although this procedure improved reliability and reduced individual interpretation bias, manual classification still involved interpretive judgment and is acknowledged as a study limitation.

3. Results and Discussion

3.1. Scientometric Analysis

3.1.1. Annual Publication Trend

As illustrated in Figure 2, the annual publication trend is presented from 2018 onward because only a limited number of relevant studies were published before that year. The figure reveals a distinct phased growth pattern in scholarly interest in AI applications within construction supply chains. Publication volumes were initially low, indicating that the field remained largely exploratory during its early development. Since 2021, however, scholarly output has increased substantially, reflecting the growing attention to digital transformation, intelligent optimization, and supply chain resilience in construction [24]. It should be noted that the apparent decrease in 2026 does not necessarily indicate a real decline in research interest, because the bibliographic search was conducted in April 2026 and the resulting dataset therefore contains only partial-year publication data. Accordingly, the 2026 value should be interpreted as a data-collection artifact rather than evidence of a downward trend. Overall, the publication trajectory suggests that AI-enabled construction supply chain research has moved from scattered exploratory studies toward a more active and diversified research domain, particularly regarding the convergence of AI with complementary technologies, including BIM and IoT [25,26]. This trend also reflects a shift in research emphasis. Earlier studies mainly focused on algorithm testing and localized optimization within specific tasks, such as cost estimation, material prediction, or scheduling [27,28]. More recent studies increasingly examine cross-organizational coordination, supply chain integration, sustainability and resilience [29,30]. This suggests that the field is gradually moving from isolated technical applications toward more systemic and process-oriented forms of intelligent supply chain management.

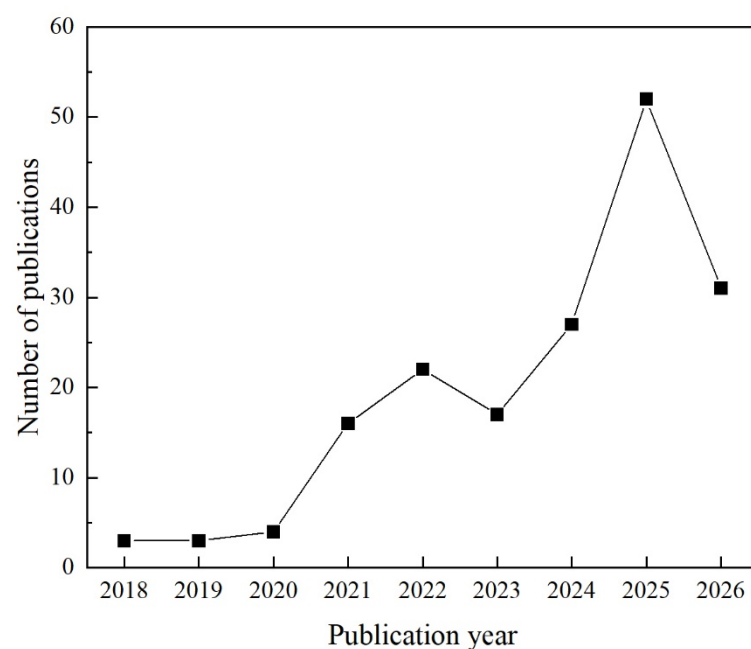


Figure 2. Annual publication trend.

3.1.2. Co-Occurrence Network Analysis

Indexed keywords were used as the analytical units for the keyword co-occurrence network analysis. The minimum occurrence threshold was set at 3. This relatively inclusive threshold was selected because the research field is still emerging and contains several specialized topics with limited publication frequencies. A higher threshold would have emphasized only established themes and potentially excluded recent developments, whereas a lower threshold would have produced a highly dispersed network containing many isolated or weakly connected terms. Under the selected threshold, 37 of the 719 identified keywords were retained, providing a manageable network while preserving thematic diversity. A custom thesaurus file was developed to standardize abbreviations, singular and plural forms, hyphenation, synonyms, and British and American spelling variants. For example, “AI” was merged with “artificial intelligence,” while “building information modeling,” “building information modelling,” and “BIM” were consolidated. Conceptually distinct terms were retained separately. Table 2 lists the prominent themes with high total link strength (≥ 10). Keyword occurrence indicates how frequently a term appeared in the analyzed records, whereas total link strength represents the cumulative strength of its co-occurrence relationships with other keywords. Figure 3 shows the resulting keyword co-occurrence network.

Table 2. Most prominent keywords in AI-enabled construction supply chain research (total link strength ≥ 10).

Keyword	Occurrences	Total Link Strength
Construction supply chain	47	62
Construction projects	35	53
Optimization	33	50
Artificial intelligence	34	47
Sustainable development	24	36
Machine learning	33	34
Genetic algorithm	19	29
Procurement	9	16
Natural language processing	9	15
Prefabricated construction	11	15
Deep learning	9	14
Engineering, procurement, construction	8	12
Particle swarm optimization algorithm	8	11
Project scheduling	5	11

The keyword co-occurrence network reveals six interrelated thematic clusters. Rather than representing separate research areas, these clusters indicate how AI-enabled construction supply chain research has developed around several partially connected knowledge domains. Overall, the network suggests that the field is still dominated by optimization-oriented and technology-driven studies, while organizational, governance, and implementation-related issues remain less strongly connected to the core keyword structure. In the VOSviewer visualizations, node size indicates the relative prominence of an item, links represent the strength of its relationship with other items, and colors denote cluster membership; therefore, each cluster can be interpreted as a group of closely related themes, sources, documents, or collaborators.

Cluster 1 (red) links construction supply chain research with sustainable development, off-site construction, production scheduling, and carbon-related concerns. This cluster indicates that sustainability has become an important lens for studying AI-enabled construction supply chains [31,32]. However, the connections are still concentrated around production scheduling, carbon footprint assessment, and prefabrication. Broader sustainability issues, such as supplier governance, social sustainability, circular procurement, and

lifecycle accountability, remain less visible. This suggests that the sustainability agenda in AI-enabled construction supply chains is still more technically and environmentally oriented than socio-organizationally integrated.

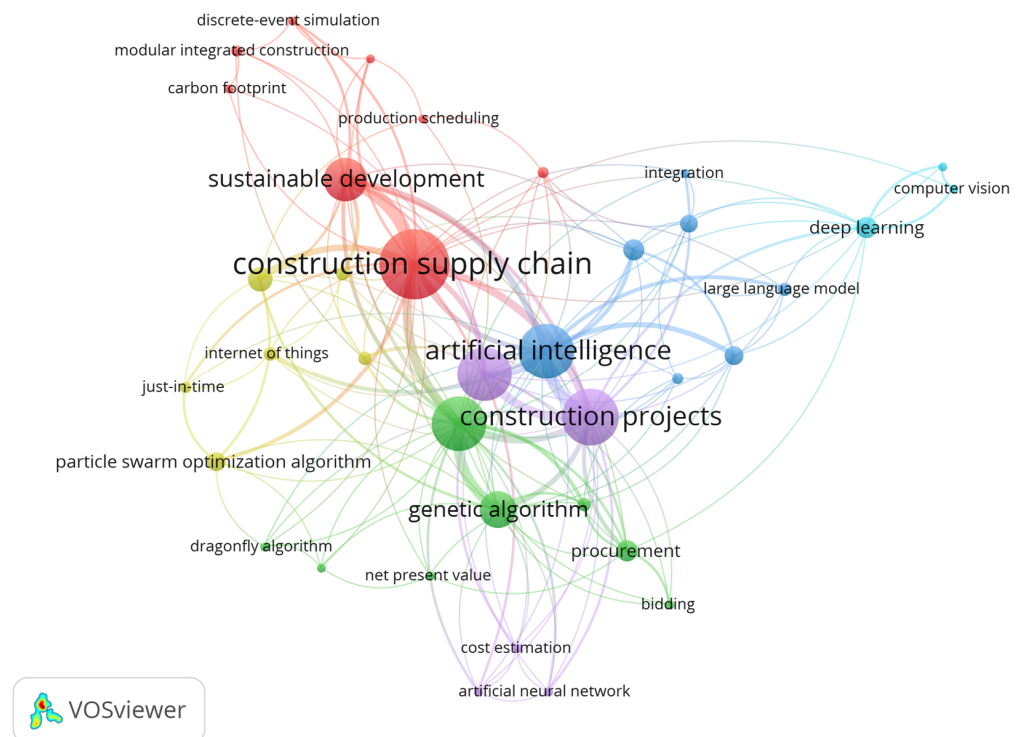


Figure 3. Keyword co-occurrence analysis.

Cluster 2 (blue) connects artificial intelligence with BIM, large language models, integration, and decision support systems. This cluster reveals the emerging role of AI as an integrative layer over existing construction digital platforms [30,33]. However, the network also suggests that digital integration is still discussed mainly at the technological level. The links between AI-enabled digital integration and practical supply chain governance, contractual coordination, liability allocation, and inter-firm data sharing remain underdeveloped. This indicates a gap between the technical promise of AI-BIM/IoT integration and the institutional conditions required for cross-organizational implementation [26].

Cluster 3 (green) is centered on optimization, genetic algorithms, procurement, inventory control, and other meta-heuristic approaches. This cluster reflects the strong influence of operations research in the field. Existing studies have made substantial progress in modeling procurement, inventory, scheduling, and resource allocation problems [34,35]. However, many of these models are developed under simplified assumptions and are often validated through simulations rather than real construction supply chain data. Therefore, the cluster reveals a methodological strength but also a practical limitation: optimization models are well developed, but their transferability to uncertain, fragmented, and multi-stakeholder construction environments remains insufficiently examined.

Cluster 4 (purple) combines machine learning, construction projects, cost estimation, regression analysis, and artificial neural networks. This cluster shows that prediction-oriented research forms another major knowledge base. Machine learning has been widely used to estimate costs, forecast demand, and support early-stage decision-making [27,32]. Nevertheless, this cluster is only weakly connected with governance, resilience, and lifecycle collaboration themes. This indicates that predictive AI is often treated as a decision-support tool for specific project tasks rather than as part of a broader supply chain coordination mechanism.

Cluster 5 (yellow) connects particle swarm optimization, IoT, just-in-time delivery, and circular economy. This cluster reveals a growing interest in real-time data collection and dynamic coordination [25]. Compared with traditional optimization studies, IoT-enabled approaches provide stronger potential for linking physical material flows with digital decision-making [36]. However, the network suggests that just-in-time delivery and the circular economy remain only partially connected. Future research should further examine how AI and IoT can jointly support closed-loop material flows, reverse logistics, waste recovery, and lifecycle resource optimization.

Cluster 6 (cyan) focuses on deep learning, computer vision, and construction and demolition waste. This cluster indicates that visual AI is emerging as a promising tool for monitoring unstructured construction environments and supporting waste identification, material tracking, and recycling assessment [37]. However, the relative isolation of this cluster suggests that computer vision applications are still mainly task-specific. Their integration with procurement systems, logistics platforms, inventory databases, and sustainability reporting remains limited. This points to an important future direction: transforming visual recognition outputs into actionable supply chain intelligence [38].

Taken together, the clusters show that the field is driven mainly by prediction, optimization, and monitoring technologies. Although digital integration, sustainability, and resilience are gaining attention, their connections with organizational governance, procurement, logistics, inventory, and cross-organizational collaboration remain limited. Future research should therefore move beyond isolated applications, toward integrated, transparent, and resilient AI-enabled construction supply chain systems.

3.1.3. Cited Source Co-Citation Analysis

Cited source co-citation analysis was used to identify the principal intellectual foundations of AI research in construction supply chains. A minimum citation threshold of 15 was applied, retaining 43 of 4517 cited sources. This threshold balanced source coverage with network clarity and should not be interpreted as an absolute measure of source quality. A source-title thesaurus was manually developed to standardize verified journal-name variants and abbreviations. For example, “J Clean Prod” and “J. Cleaner Prod.” were consolidated under “*Journal of Cleaner Production*.” As shown in Figure 4 and Table 3, *Automation in Construction*, *Journal of Cleaner Production*, *Journal of Construction Engineering and Management*, *Sustainability*, and *Buildings* occupy central positions in the network. Citation counts indicate how frequently each journal was cited, whereas total link strength reflects the cumulative strength of its co-citation relationships. Journals with high values on both measures can therefore be considered influential and intellectually central publication venues.

Table 3. Top 10 journals by citation and total link strength.

Journal Source	Number of Citations	Total Link Strength
Automation in Construction	480	7902
Journal of Cleaner Production	409	7878
Journal of Construction Engineering and Management	390	5609
Sustainability	198	4354
Buildings	131	2453
Computers and Industrial Engineering	121	2222
Journal of Building Engineering	90	2134
International Journal of Production Research	91	1960
Resources, Conservation and Recycling	72	1933
Construction Management and Economics	77	1737

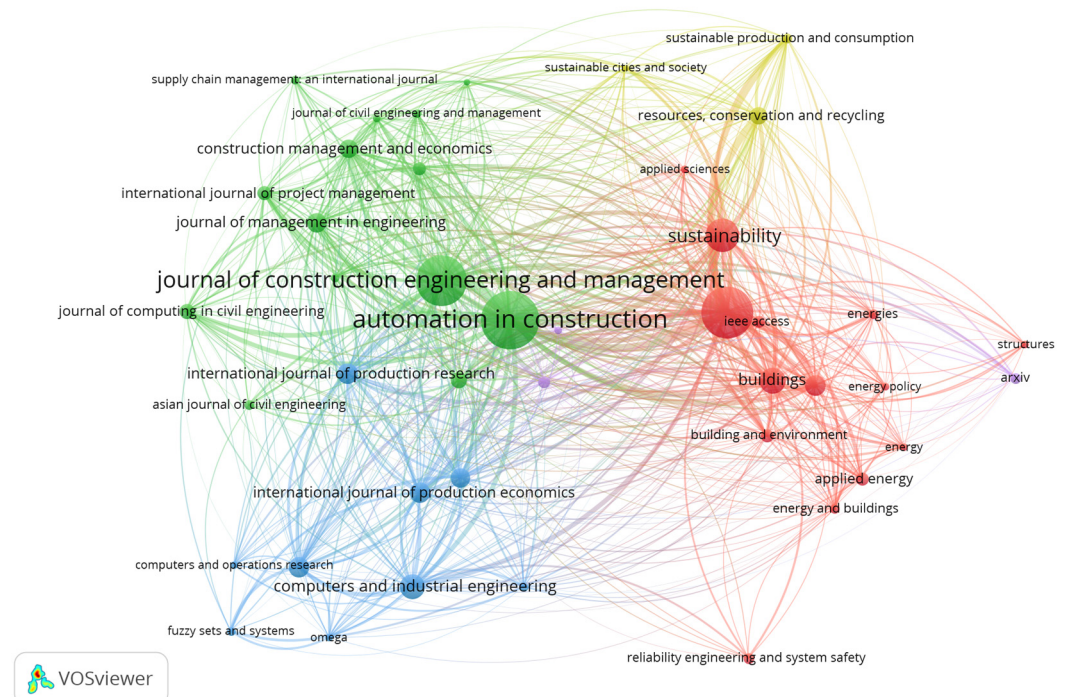


Figure 4. Cited source co-citation analysis.

3.1.4. Document Citation Analysis

For the document citation analysis, a minimum citation threshold of 10 retained 96 of the 212 reviewed articles. This threshold balanced the identification of influential studies with broad coverage of a relatively recent field, while limiting bias toward older publications and avoiding an overly dense network. Mocanu et al. [28] emerged as the most highly cited publication, followed by Kumaraswamy and Dissanayaka [39] and Elghaish et al. [40]. These studies mainly emphasize machine learning and intelligent optimization for forecasting, resource scheduling, and dynamic decision-making, particularly in prefabricated and modular construction. The integration of AI with IoT and BIM also supports engineering data analysis, real-time logistics monitoring, and automated business processes. Sustainability-related studies further apply data-driven models to embodied carbon prediction and material lifecycle optimization. As shown in Figure 5, these citation patterns indicate a shift toward more integrated, adaptive, and sustainable construction supply chain systems, driven by interdisciplinary research and technological convergence.

3.1.5. Analysis of Collaborative Networks of Authors and Countries

Visualizing research collaboration networks provides an intuitive map of the intensity of academic interactions among scholars and countries and helps identify the principal contributors within a research domain. In academic research, co-authorship collaboration is recognized as a primary driver of knowledge advancement and scientific productivity [23]. As illustrated in the author collaboration network (Figure 6), 697 authors have participated in research on AI within the construction supply chain, yet only 53 have published more than one paper. This highly dispersed, low-cohesion publication pattern indicates that research within this domain remains in a nascent, exploratory phase. The relative scarcity of high-output scholars and the absence of a tightly knit collaborative infrastructure further highlight the current fragmentation of research capabilities. This pattern is consistent with innovation diffusion theory [41], which suggests that knowledge production in emerging fields is initially concentrated among a small group of pioneers. It also reflects institutional theory [42], as collaboration may be constrained by local research policies, funding priorities,

and regulatory environments, resulting in territorial clustering. These findings highlight the need for more coordinated and interdisciplinary research collaboration.

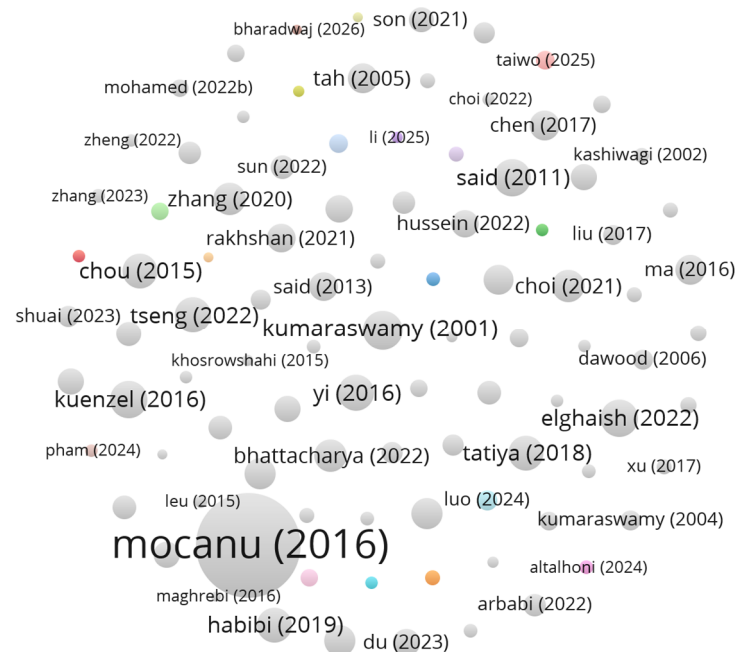


Figure 5. Document citation analysis. The principal labeled documents include Mocanu (2016) [28], Kumaraswamy (2001) [39], and Elghaish (2022) [40].

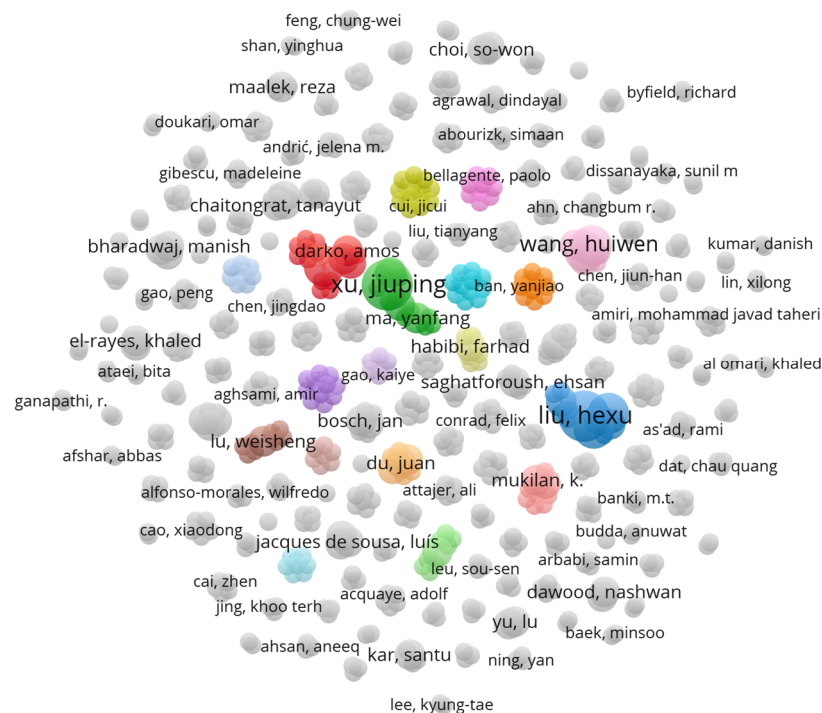


Figure 6. Co-authorship network generated by the authors using VOSviewer [21] from the bibliographic dataset of 212 articles analyzed in this study.

These observations regarding research fragmentation and territorialization are further corroborated by the national-level collaboration network (Figure 7). Within this network, nodes represent individual countries, with node size reflecting the volume of scholarly research output. The empirical data indicate that China leads with 59 publications, followed by the United States with 30, while the United Kingdom and India demonstrate moderate

academic activity. Although network edges, which signify the intensity of transnational collaboration, indicate that preliminary academic ties have been established among certain nations, the overall network density remains low. Furthermore, substantial collaboration remains concentrated among a small number of research-intensive countries. This disparity suggests that although AI applications within the construction supply chain have garnered widespread international attention, a globally integrated research network has not yet emerged. Given the complex global socio-technical structure of construction supply chains, it is important to address institutional and cultural differences and foster deeper cross-border academic exchange and data sharing, thereby strengthening the intellectual foundation for theoretical advancement and international engineering practice.

3.1.6. Integrated Implications of the Scientometric Patterns

Taken together, the publication, keyword, citation, and collaboration patterns indicate that AI research in construction supply chains remains predominantly technology- and task-oriented. Optimization, machine learning, prefabrication, sustainability, and computer vision are central themes, and existing studies are strong in explaining how AI improves forecasting, scheduling, classification, and resource allocation. However, weak links with governance, contractual coordination, organizational behavior, human judgment, and lifecycle accountability reveal fragmented theoretical development. Future research should therefore move beyond isolated algorithm–performance relationships and examine how AI interacts with data infrastructures, organizational routines, inter-firm relationships, institutional rules, and human decision-making.

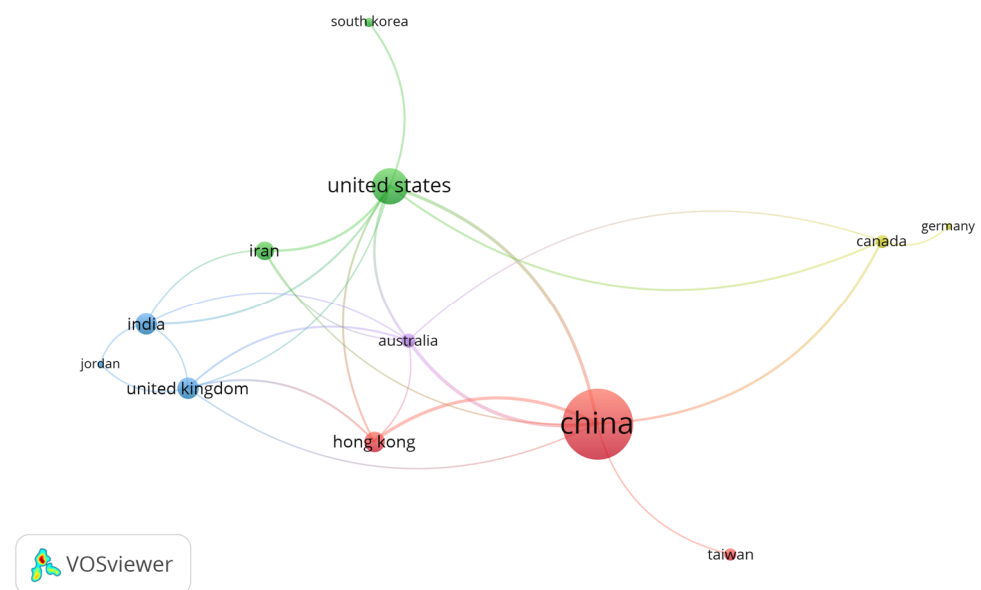


Figure 7. A network of cooperation between countries.

The co-citation and document citation patterns show that the field draws on construction engineering, production and operations research, sustainability, and digital technology research. Although this interdisciplinary foundation supports both technical optimization and managerial coordination, influential studies remain concentrated on machine learning, optimization algorithms, BIM, IoT, and prefabricated construction. Less structured issues, including trust, negotiation, liability, supplier behavior, workforce acceptance, and power asymmetry, receive less attention. This imbalance highlights the need to connect computational models with socio-technical and inter-organizational explanations of supply chain performance.

From a practical perspective, forecasting, logistics optimization, inventory monitoring, visual inspection, and document processing represent relatively mature entry points for AI adoption. However, successful task-level applications do not automatically create cross-organizational value. System-level implementation also depends on data interoperability, process redesign, stakeholder participation, model explainability, and clear allocation of decision authority and accountability. Managers should therefore assess AI not only by model accuracy and computational efficiency but also by its compatibility with existing workflows, data systems, contractual arrangements, and user capabilities.

The low density of author and country collaboration further indicates dispersed knowledge production and limited cumulative learning across regions and disciplines. This fragmentation may hinder replication, shared benchmark datasets, and the transferability of AI models across project, regulatory, and market contexts. Future studies should promote cross-country and interdisciplinary collaboration through shared datasets, common evaluation protocols, multi-project field experiments, and longitudinal studies.

Overall, future research should connect prediction and optimization with resilience and organizational governance, integrate computer vision and IoT-based monitoring with procurement, logistics, and lifecycle material management, and incorporate the environmental footprint, economic feasibility, and human consequences of AI implementation into sustainability research. Such integration would advance the field from fragmented algorithmic applications toward theoretically grounded and practically implementable AI-enabled construction supply chain systems.

3.2. Qualitative Content Synthesis

3.2.1. Applications of AI in Construction Supply Chains

To organize the application evidence, the eight categories are mapped onto five interconnected stages of the construction supply chain lifecycle: (1) front-end planning, bidding, and procurement; (2) off-site production and supplier coordination; (3) transportation and site delivery; (4) on-site construction and material use; and (5) operation, maintenance, reverse logistics, and end-of-life recovery. Bidding and procurement, prefabricated component production, logistics and transportation scheduling, and material and inventory management are mainly associated with specific operational stages. In contrast, organizational collaboration, risk and resilience management, green supply chain management, and performance evaluation and decision support function as cross-lifecycle capabilities connecting stakeholders, data flows, material flows, and decisions across project phases.

These categories are not mutually exclusive. Material management, for example, extends from demand forecasting and procurement to transportation, on-site consumption, reuse, recycling, and disposal, while risk management and decision support influence multiple lifecycle stages. Table 4 summarizes these relationships.

The mapping shows that existing research is concentrated on front-end planning, production, logistics, and construction execution, particularly procurement optimization, production scheduling, transportation routing, and material monitoring. By contrast, operation and maintenance, reverse logistics, component reuse, remanufacturing, and end-of-life recovery remain underexplored. Many studies also optimize individual stages without considering downstream effects. Future research should therefore develop lifecycle-connected AI models that assess upstream and downstream trade-offs rather than isolated supply chain activities.

Table 4. Mapping AI application categories to the construction supply chain lifecycle.

Supply Chain Lifecycle Stage	Main Supply Chain Activities	Corresponding AI Application Categories	Representative AI Functions
Front-end planning, bidding, and procurement	Demand assessment, bid evaluation, supplier selection, contract review, purchasing decisions	Bidding and procurement; decision support; risk and resilience management	Demand forecasting, bidder prediction, supplier evaluation, contract extraction, cost and risk assessment
Off-site production and supplier coordination	Component manufacturing, outsourcing, production scheduling, workforce and capacity allocation	Prefabricated component production; organizational collaboration; decision support	Production optimization, outsourcing decisions, resource scheduling, quality prediction
Transportation and site delivery	Vehicle routing, fleet allocation, shipment monitoring, just-in-time delivery	Logistics and transportation scheduling; risk and resilience management	Dynamic routing, delivery prediction, fleet optimization, disruption warning
On-site construction and material use	Material acceptance, inventory control, consumption monitoring, resource allocation, execution coordination	Material and inventory management; organizational collaboration; decision support	Computer vision monitoring, quantity estimation, inventory forecasting, labor and resource allocation
Operation, maintenance, reverse logistics, and end-of-life	Asset monitoring, maintenance planning, reuse, recycling, waste sorting, disposal	Green supply chain management; material management; risk and resilience management	Predictive maintenance, lifecycle tracking, waste classification, reverse-logistics optimization
Cross-lifecycle integration	Data exchange, stakeholder coordination, performance control, sustainability and governance	Organizational collaboration; risk and resilience; green supply chain management; comprehensive decision support	BIM/ERP/IoT integration, multi-agent coordination, carbon accounting, explainable and multi-objective decision support

Bidding and Procurement in Construction Supply Chains

As the initial stage of the construction supply chain, tendering and procurement directly affect cost control and project delivery quality. The reviewed studies suggest that AI may support a gradual shift from experience-based processes toward more predictive and data-driven decision-making in tender evaluation, supplier selection, procurement execution, and contract management. In tender decision-making, AI-driven multi-objective optimization can incorporate time, cost, quality, energy, environment, and safety to support sustainable construction decisions [43]. Machine learning can also predict bidder participation, competitive intensity, and project costs using key economic variables [44].

In supplier selection and procurement execution, machine learning can evaluate suppliers using historical performance, financial health, quality metrics, and capacity constraints, thereby supporting vendor management and material ordering decisions [45]. AI can also translate design information into procurement requirements [46], integrate with ERP systems to improve scheduling and supplier collaboration [47], and combine inventory, consumption, and site data to dynamically adjust procurement batches and order volumes, reducing material shortages and excessive inventory [29].

In procurement contract management, generative AI can extract key performance clauses and commercial information from complex contracts, supporting automated querying, greater processing efficiency, improved accuracy, and regulatory compliance [48]. Overall, the reviewed studies suggest that AI may support a gradual shift in bidding and procurement toward more predictive, data-informed, and compliance-oriented processes. However, existing studies mainly improve discrete tasks such as supplier evaluation, bid

prediction, and contract extraction, while paying less attention to procurement governance, supplier relationships, and accountability across the full supply chain.

The Production of Prefabricated Components in Construction Supply Chains

Recent studies have introduced new AI-supported optimization approaches for manufacturing operations within prefabricated construction supply chains. For instance, Tao et al. [49] incorporated outsourcing decisions and multi-skilled worker constraints into a unified optimization framework, systematically addressing two highly interdependent subproblems: the determination of outsourced order volumes and the scheduling of in-house orders across parallel production lines. Using an integer linear programming model and an efficient deep Q-network algorithm, this study demonstrated that the proposed approach could mitigate dynamic uncertainty in large-scale and complex scenarios. Compared with traditional empirical heuristics, this algorithmic approach can reduce operational costs and support the core objectives of prefabrication enterprises: improving production efficiency while controlling expenditure.

Furthermore, the reviewed literature indicates a gradual shift from single-facility scheduling models toward frameworks that jointly consider production, inventory, and logistics decisions. Li et al. [50] used multi-scenario simulation to examine how production–sales balance, production rates, warehousing capacity, and information sharing affect project duration, lifecycle costs, and carbon emissions. The study supports coordinated scheduling across module production, logistics, and on-site assembly while balancing economic efficiency and environmental sustainability.

Overall, AI-enabled frameworks can coordinate scheduling, outsourcing, inventory, logistics, and on-site assembly within a unified optimization framework for prefabricated production. However, existing models remain stronger in computational development than in empirical validation under real factory–site coordination conditions.

Logistics and Transportation Scheduling in Construction Supply Chains

AI-based methods have increasingly been used to improve logistics and transportation scheduling in complex construction environments. By integrating geographic information systems (GIS), real-time traffic data, and predictive road network models, AI can dynamically optimize vehicle routing across multi-fleet and multi-node networks, mitigate congestion risks, support more reliable just-in-time delivery [25,51], and reduce transportation costs, empty hauls, and logistics-related emissions [50].

For perishable materials, hybrid meta-heuristic algorithms combining the grey wolf optimizer and the dragonfly algorithm can coordinate distributed production with dynamic site consumption, improving multi-point supply coordination and supply chain resilience [35]. Multi-agent systems can also automate ERP workflows and integrate reinforced concrete component procurement and transportation [47]. When combined with artificial neural networks, they can evaluate fleet configurations and optimize trade-offs among carbon emissions, logistics costs, and project duration [52]. Other studies have applied genetic algorithms to integrate project portfolio selection, operations scheduling, and material sequencing, substantially reducing computation time while maintaining solution quality [45]. Integrated procurement-scheduling models further support cost and emission control across production, transportation, and construction [53]. For modular integrated construction, hybrid deep learning models combining convolutional neural networks and recurrent neural networks can analyze multi-sensor logistics data and provide early warnings of transport-related structural damage [54].

Overall, AI can improve routing, fleet allocation, just-in-time delivery, cost control, emission reduction, and transport risk management. However, existing studies differ in

their assumptions regarding real-time data availability and operational control. Future research should therefore examine the organizational feasibility of implementing AI-based logistics decisions across contractors, suppliers, transport firms, and site managers.

Materials and Inventory Management in Construction Supply Chains

The reviewed studies suggest that AI-based forecasting and sensing tools can improve on-site material and inventory management. By analyzing historical maintenance and procurement data, AI models can forecast material demand and maintenance costs, supporting delivery planning, inventory optimization, supply chain resilience, and data-driven budgeting [55]. Advanced rotating object detection algorithms can also improve the accuracy and real-time performance of material recognition, providing a basis for precision inventory control [37].

Bulk materials, including sand, gravel, cement, and concrete-related inputs, constitute a substantial share of construction material expenditure. To manage these critical resources, recent scholarship has introduced hybrid visual detection frameworks integrating RGB cameras and LiDAR sensors. Within these systems, YOLOv5 supports automatic material classification with 81.6% accuracy, while PointNet++ enables three-dimensional volumetric measurement with less than 8% deviation. These technologies reduce reliance on manual quantification and improve material acceptance and on-site consumption monitoring [29]. AI-powered IoT systems further support lifecycle material tracking across procurement, construction, operation, and maintenance, while enabling intelligent construction waste sorting and reducing material loss and disposal costs [26]. Predictive models can also evaluate how material composition and design parameters affect end-of-life strategies, supporting design-for-disassembly and recycled material use while strengthening lifecycle data traceability [56].

Overall, AI can improve material visibility, reduce manual measurement, and enhance inventory control. However, stronger integration is needed among material recognition, procurement planning, inventory databases, and lifecycle traceability.

Organizational Collaboration and Process Automation in Construction Supply Chains

AI supports cross-organizational collaboration and process automation across the project lifecycle by integrating operations, information, and relationships, thereby improving supply chain performance [57]. Integrated frameworks combining AI, smart contracts, and standardized classification systems can connect data flows from design to final settlement and support continuous cost estimation and monitoring [26,58]. BIM-based predictive models using Elman neural networks can also respond to design changes and supply chain cost fluctuations, advancing automated cost management [59].

Multi-agent systems integrating compact large language models with model context protocols can automate ERP workflows for structural components from specification approval to manufacturing and delivery while creating closed-loop communication between AI agents and human stakeholders [47]. Generative AI further supports proposal generation, planning optimization, and contract processing [48], while standardized task classifications clarify responsibilities and reduce communication redundancy [60]. AI also enables dynamic labor allocation through the non-dominated sorting genetic algorithm II (NSGA-II) [61] and automates on-site processes such as bricklaying through robotic systems [62]. In summary, the reviewed studies indicate that AI-based tools may support more integrated forms of collaboration in a construction industry traditionally characterized by fragmented processes. Through integrated data flows, closed-loop multi-agent communication, and software–hardware automation, these tools may improve coordination across selected supply chain activities.

Overall, AI can connect design, procurement, production, delivery, and settlement processes through integrated data flows, multi-agent communication, and software and hardware automation. However, existing research pays less attention to behavioral resistance, inter-organizational trust, data ownership, and contractual incentives, indicating that organizational collaboration is not only a technical integration issue but also a governance and institutional design problem.

From a socio-technical perspective, AI does not eliminate the role of planners, procurement professionals, logistics coordinators, project managers, and frontline workers. These actors remain essential for interpreting contextual information, handling unexpected events, balancing competing objectives, and assuming final responsibility. Effective AI-supported workflows therefore depend on user skills, transparency, training, trust, workforce acceptance, and clearly defined human oversight. AI-enabled supply chain performance ultimately results from the alignment of technology, people, organizational routines, and governance arrangements.

Risk and Resilience Management in Construction Supply Chains

AI supports risk identification, mitigation, and resilience across construction supply chains by extracting insights from large datasets and enabling lifecycle risk management [63]. Explainable AI may improve the transparency and credibility of risk predictions, thereby supporting proactive risk prevention [64], while models incorporating longitudinal disruption data enhance adaptability to macroeconomic shocks [65]. Concurrently, high-precision investment cost estimation models can reduce the likelihood of cost overruns and financial uncertainty across the asset lifecycle [66].

Robust decision-making frameworks use sensitivity analysis to identify critical risks [67] and assess how material supply fluctuations affect operational adaptability [45]. Dual-objective optimization models further combine buffer inventories and alternative suppliers to address supply bottlenecks, logistics delays, and force majeure events under different disruption intensities [68]. Advanced robotics can also reduce pathogen transmission risks and dependence on manual labor during labor shortages and public health crises [62]. For climate and environmental risks, multi-agent simulation can quantify lifecycle carbon emissions across prefabrication, transportation, and on-site assembly, supporting regulatory compliance and long-term climate resilience [52].

Overall, AI strengthens early warning, robust optimization, and disruption response. However, although many studies simulate risk scenarios, fewer validate AI-enabled resilience mechanisms in real construction supply chains exposed to material shortages, policy shifts, market volatility, or extreme weather events.

Green Supply Chain Management and Sustainability in Construction Supply Chains

Driven by global carbon-reduction objectives, AI supports the sustainability and green transition of construction supply chains by analyzing environmental, social, and governance data and providing strategic pathways toward circular economy practices [69,70]. Reviewed studies show that intelligent technologies can reduce material overconsumption, support life cycle assessment, and improve environmental evaluation of emerging construction methods. By compiling comprehensive datasets for robotic timber construction, these frameworks precisely quantify operational energy consumption and environmental impacts [71]. To facilitate the initial stages of low-carbon transitions, scholars increasingly use life cycle assessment tools to optimize the full-chain environmental performance of architectural designs and minimize material consumption [72]. During the physical construction phase, the deployment of robotic technologies enables precision control over material utilization. For instance, automated bricklaying systems have successfully re-

duced mortar waste by 15% [62]. Integrated BIM, AI, and radio-frequency identification architectures may also reduce material waste and landfill demand [26].

AI further supports carbon management through data-driven prediction. Dynamic emission models can quantify the effects of regional and seasonal variables on concrete-related carbon emissions, helping enterprises optimize mix designs, select low-carbon materials, and improve logistics planning [73]. However, AI's environmental contribution should be assessed from a lifecycle perspective because model training, fine-tuning, deployment, and inference consume electricity, cooling resources, and computing hardware. These impacts are especially relevant for large deep learning and generative AI models. Therefore, reductions in transportation, material use, waste, and operational emissions should be evaluated against the computational and implementation demands of AI systems [48,74]. In summary, AI can support the construction supply chain's transition away from energy-intensive and resource-inefficient management practices, toward greener, low-carbon, and circular development.

Overall, AI can support carbon accounting, waste reduction, design-for-disassembly, and circular material management. However, existing studies emphasize environmental indicators more than economic, social, and governance dimensions. Future research should examine how AI-enabled green supply chain management balances carbon reduction, cost feasibility, supplier participation, and regulatory compliance.

Performance Evaluation and Comprehensive Decision Support in Construction Supply Chains

Performance evaluation and decision support are central objectives of intelligent construction supply chain management. AI-based tools can process large, complex datasets and support data-driven evaluation of cost, schedule, carbon emissions, logistics, and risk. Existing studies show that AI can improve systemic performance through supply chain integration [57], while hybrid models combining multi-agent systems and deep learning can identify optimal configurations under multiple objectives and risk constraints [52]. Spatio-temporal forecasting models further support green procurement, carbon accounting, and industrial decarbonization policies [73].

In investment budgeting and bidding, AI-based forecasting can improve financial projections under market volatility and supply chain disruption [65]. Small-sample machine learning models have also been applied to specialized projects, achieving 97.1% accuracy in investment estimation [66], while intelligent systems can support bid baseline setting and tender resource allocation [44].

AI further supports material delivery planning, labor allocation, production scheduling, and resilience strategies through multi-objective optimization, meta-heuristic algorithms, and NSGA-II [49,67,68]. Multi-agent systems can also generate interpretable analytical reports, reduce manual processing and collaboration errors, and preserve final decision-making authority for human engineers [47].

Overall, AI-based tools may help transform fragmented project data into actionable recommendations and support a shift from experience-based management toward data-informed management. However, future research should move beyond model accuracy to examine explainability, managerial trust, accountability, and how decision authority is distributed between AI systems and human managers.

Across the reviewed studies, AI applications in construction supply chains can be synthesized into five functional roles: prediction, optimization, monitoring, coordination, and governance support. Together, these roles reflect a broader shift from experience-based decision-making toward data-driven and algorithm-supported supply chain management.

First, prediction-oriented studies apply machine learning to material demand, cost estimation, bidder participation, maintenance needs, and carbon emissions. Although these models can improve forecasting under nonlinear and data-intensive conditions, their performance depends heavily on data quality, sample representativeness, and contextual transferability.

Second, optimization-oriented studies address procurement, prefabricated production, logistics routing, inventory control, labor allocation, and resilience strategies. Meta-heuristic algorithms, reinforcement learning, and multi-objective optimization can reduce costs and support the balancing of time, carbon emissions, and risk. However, many models remain simulation-based and rely on simplified assumptions, creating a gap between algorithmic optimality and practical implementation.

Third, monitoring-oriented studies use computer vision, IoT, RFID, LiDAR, and sensor-based systems to improve visibility into material flows, inventory, transportation activities, and construction waste. These technologies can reduce manual inspection and provide timely information, but their value depends on integration with procurement, logistics, scheduling, and decision-support systems.

Fourth, coordination-oriented studies combine AI with BIM, ERP, smart contracts, digital twins, large language models, and multi-agent systems to reduce information fragmentation and support cross-organizational collaboration. Nevertheless, existing research emphasizes technical integration more than the institutional, contractual, and behavioral conditions required for data sharing, trust, and coordinated action.

Finally, governance-oriented studies address explainable AI, cybersecurity, ethical risks, liability allocation, and multi-stakeholder decision-making, but remain less developed than prediction and optimization research. The reviewed literature increasingly recognizes that AI adoption in construction supply chains is not only a technical problem but also a governance challenge. This highlights the need for greater attention to explainability, accountability, data ownership, human–AI collaboration, and the allocation of risks and responsibilities.

To provide a more transparent comparison of the evidence base, Table 5 compares the reviewed studies by dominant AI technique, supply chain process, principal data type, validation method, and relative practical maturity. Practical maturity is assessed comparatively rather than as a formal technology-readiness level. “Emerging” refers primarily to conceptual frameworks, prototypes, or simulation-based studies; “intermediate” indicates repeated computational or case-based validation but limited cross-project transferability; and “relatively mature” indicates more frequent use of operational or field data and clearer pathways toward practical deployment.

Table 5 indicates that the practical maturity of AI applications remains uneven. The evidence base is strongest for task-level prediction, optimization, and monitoring. Machine learning models using structured historical data, optimization methods for bounded problems, and computer vision systems for specific tasks have accumulated comparatively stronger validation. By contrast, generative AI, multi-agent coordination, explainable governance systems, and cross-lifecycle integration remain at earlier stages. Future research should therefore prioritize longitudinal field validation, cross-project transferability, organizational adoption, and lifecycle value assessment.

Table 5. Summary classification of AI applications in construction supply chains.

AI Technique	Main Supply Chain Process	Principal Data Type	Common Validation Method	Relative Practical Maturity
Machine learning and neural networks	Demand forecasting, cost estimation, bidder participation, maintenance and carbon prediction	Historical project, cost, procurement, market, and environmental data	Train–test evaluation, comparative accuracy testing, case studies	Intermediate to relatively mature
Meta-heuristic and multi-objective optimization	Procurement planning, supplier selection, production scheduling, inventory control, logistics and resilience planning	Structured operational parameters, schedules, costs, capacity and disruption scenarios	Computational experiments, scenario analysis, benchmark comparison	Intermediate
Reinforcement learning and deep Q-networks	Prefabricated production, outsourcing, dynamic scheduling and resource allocation	Simulated production states, real-time operational variables and decision rewards	Simulation, algorithm comparison, sensitivity analysis	Emerging to intermediate
Computer vision and deep learning	Material recognition, inventory measurement, quality inspection, waste identification and site monitoring	Images, video, RGB, LiDAR and point-cloud data	Detection accuracy, field demonstrations, prototype testing	Intermediate to relatively mature
Natural language processing and generative AI	Contract review, tender-document extraction, proposal generation and information retrieval	Contracts, tender documents, specifications, reports and ERP text records	Prototype evaluation, retrieval accuracy, case demonstrations	Emerging to intermediate
IoT- and sensor-enabled AI	Material tracking, transportation monitoring, structural-condition assessment and predictive maintenance	RFID, sensor streams, GPS, traffic, equipment and environmental data	Prototype deployment, case studies, real-time system testing	Intermediate
Multi-agent systems and agentic AI	ERP coordination, logistics collaboration, stakeholder communication and integrated decision support	Multi-source BIM, ERP, IoT, logistics and project-management data	Simulation, system prototypes and limited project demonstrations	Emerging
AI–BIM/digital twin integration	Cross-process information integration, lifecycle monitoring, logistics simulation and risk visualization	BIM models, digital twins, schedules, quantities, sensor and asset data	Framework development, prototypes and case-based validation	Emerging to intermediate
Explainable AI and governance-oriented systems	Risk assessment, accountable decision support and human–AI collaboration	Risk records, project performance data and model explanation outputs	Model-explanation analysis, user evaluation and conceptual frameworks	Emerging
Robotics and autonomous systems	Automated construction, material handling and production execution	Sensor, vision, motion-control and operational performance data	Physical experiments, pilot demonstrations and lifecycle assessment	Intermediate

3.2.2. Barriers to AI Integration into Construction Supply Chains

The construction industry has long faced productivity challenges that contribute to rising costs and delivery inefficiencies [75]. AI implementation in construction supply chains is constrained by five interconnected barriers: technological and data barriers, human and organizational barriers, economic and firm-capability barriers, inter-organizational and interoperability barriers, and legal, ethical, and cybersecurity barriers. Together, these barriers determine whether AI applications can progress from isolated pilots to sustained implementation across construction supply chains.

Technological and data barriers. AI depends on accurate, consistent, representative, and accessible data. However, construction data are often incomplete, fragmented, stored in incompatible formats, and collected under non-standardized conditions [76]. Biased samples, inconsistent labeling, and changing site conditions further limit model reliability and transferability across projects, firms, and regions. Practical implementation therefore requires data-quality protocols, benchmark datasets, continuous model validation, and performance monitoring.

Human and organizational barriers. Conservative organizational cultures, labor-intensive practices, and established professional routines may create resistance to AI-enabled workflow redesign [77,78]. Employees may also lack the skills needed to interpret algorithmic outputs or may perceive AI as a threat to professional autonomy, established roles, and job security. Black-box models can further weaken trust and managerial confidence [79]. Addressing these barriers requires role-specific training, participatory system design, explainable outputs, clear decision authority, and human oversight. AI adoption should therefore be treated as an organizational change process rather than merely a technological investment.

Economic and firm-capability barriers. AI implementation requires investment in infrastructure, data management, software integration, cybersecurity, specialized personnel, model updating, and maintenance. Uncertain returns and limited lifecycle evidence may discourage adoption, particularly among small and medium-sized enterprises. SMEs often have less-developed data infrastructure, limited digital expertise, tighter financial constraints, and lower bargaining power within shared platforms. Phased pilots, modular applications, cloud-based services, shared platforms, and targeted financing and training may therefore be more feasible than uniform implementation.

Inter-organizational and interoperability barriers. Construction supply chains involve temporary organizations, fragmented responsibilities, heterogeneous systems, and dispersed data ownership. Differences in software, data structures, classification systems, and governance arrangements hinder the integration of design, procurement, production, transportation, inventory, and site data. Reluctance to share commercially sensitive information further limits cross-organizational AI applications [80]. Integration with BIM, ERP, IoT, and digital twins is also constrained by incompatible schemas, proprietary platforms, inconsistent semantic definitions, and limited exchange standards. Wider implementation requires common data standards, semantic taxonomies, validated exchange protocols, contractual data-sharing rules, and clear platform governance.

Legal, ethical, and cybersecurity barriers. AI raises unresolved issues concerning data privacy, intellectual property, algorithmic bias, accountability, and liability for erroneous outputs. When AI contributes to financial losses, disputes, safety incidents, or operational disruption, responsibility among developers, providers, contractors, managers, and data owners may be unclear [48,81]. Cybersecurity risks include hacking, data poisoning, adversarial attacks, and manipulated inputs that can compromise predictions and physical supply chain operations [82]. Implementation therefore requires audit trails, access controls, data protection, adversarial testing, continuous monitoring, human escalation procedures, and explicit contractual allocation of responsibility.

These barriers reinforce one another. Poor data quality and limited interoperability reduce model reliability, weakening user trust and increasing the need for manual verification. Limited skills, unclear decision authority, and high costs further restrict workflow redesign and data sharing, while legal and cybersecurity uncertainty discourages large-scale adoption. Therefore, technical accuracy alone is insufficient. Organizations should assess data readiness, workflow compatibility, workforce capabilities, financial feasibility, interoperability, and governance risks before scaling AI. A staged socio-technical approach based on measurable use cases, human oversight, continuous monitoring, and gradual cross-organizational expansion can help transform isolated AI experiments into sustainable construction supply chain capabilities.

3.2.3. Integration of AI with Other Digital Technologies

The convergence of AI with other digital technologies provides an important foundation for intelligent construction supply chains. A single AI algorithm cannot fully address

long project lifecycles, diverse stakeholder interests, and cross-scenario requirements. By integrating AI with BIM, GIS, advanced sensor networks, sixth-generation (6G) communication technologies, blockchain, digital twins, IoT, and ERP systems, construction supply chains may support a shift from experience-based planning toward data-driven, real-time, and collaborative management.

The integration of AI and BIM can reduce information silos by supporting semantic information extraction, cross-team information exchange, and data-informed decision-making. Combining BIM with multi-objective optimization algorithms, such as NSGA-II, particle swarm optimization, and genetic algorithms, can reconcile real-world constraints and optimize resource acquisition and four-dimensional scheduling [61,83]. In lifecycle solid-waste management, BIM, AI, and predictive analytics support automated waste classification and material reduction [26]. Convolutional deep belief networks can also extract semantic insights from three-dimensional BIM geometric data, reducing manual annotation and improving data consistency and interpretability for cross-organizational decision-making [84]. However, AI–BIM integration remains constrained by limited interoperability standards and implementation frameworks. Heterogeneous data schemas, proprietary software environments, inconsistent semantic definitions, different levels of model detail, and fragmented data ownership hinder reliable data exchange and the use of BIM information for AI model training and decision support. Therefore, integration is likely to remain project-specific, platform-dependent, and limited to selected workflows until common data standards, validated exchange protocols, and cross-organizational governance mechanisms are further developed [85,86].

The integration of AI and GIS provides a macro-level decision-making paradigm for spatial supply chain scheduling and the dynamic coordination of in-transit resources. To address the complexities of cross-regional logistics, this integrated framework uses GIS-based spatial visualization and hybrid multi-agent simulation models to allocate shared resources across multiple project sites and coordinate reverse-logistics activities. Under the modeled conditions, such spatial coordination may improve synchronization among manufacturing capacity, transportation fleets, and on-site requirements, thereby supporting the implementation of just-in-time production principles within complex, multi-nodal supply chain networks [30].

The convergence of AI and advanced sensing technologies may improve the precision of material management to a micro-physical level. To address blind spots in the management of bulk materials, an Industry 4.0 solution combining RGB cameras and LiDAR sensors leverages YOLOv5 and PointNet++ deep learning models to segment features from two-dimensional images and three-dimensional point clouds, respectively. This technological integration replaces manual measurement with automated material classification and high-precision volumetric quantification, providing objective, empirical data to support procurement and on-site inventory management [29].

Furthermore, the synergy between AI and 6G communication technology may help mitigate data transmission bottlenecks, facilitating a transition from offline planning to real-time, online command and control. By leveraging the ultra-low latency and high bandwidth anticipated for 6G networks, deep neural networks may process large data streams generated by dense sensor networks. This rapid-response capability may enable AI frameworks to generate real-time dispatch recommendations in dynamic construction environments, potentially strengthening supply chain resilience under unforeseen disruptions [87].

The reviewed studies suggest that combining AI with blockchain may strengthen mechanisms for data trust and provenance within construction material supply chains. Integrated management frameworks underpinned by AI and smart contracts can synthesize

data flows from design through to final settlement. A unified standardized classification system further supports this integration. In the applications examined, this integration may improve the alignment between cost estimation and continuous monitoring across the project lifecycle [26,58]. Furthermore, the immutable nature of blockchain can provide verifiable records for critical activities, such as raw material sourcing and concrete mix design, while artificial neural networks can support material-performance simulation and design optimization, potentially reducing reliance on traditional trial-and-error methods. This combination of intelligent computation and trusted verification can help reduce cross-lifecycle information silos and support the automation and standardization of quality inspection, information verification, and liability determination [88].

The interaction between AI and digital twin technology provides the digital foundation for comprehensive supply chain risk visualization and intelligent early warning systems. Leveraging fully mirrored material-delivery networks enabled by digital twin technology, these systems achieve transparent, traceable status monitoring while providing virtual simulation environments for advanced algorithms. When combined with enhanced Hidden Markov models that account for interactions among multiple materials and equipment types, the architecture can uncover latent data correlations and predict material-delivery trajectories, helping align supply flows with on-site equipment-utilization plans. Consequently, this approach can shift monitoring from experience-based manual inspection toward proactive process integration and real-time status tracking [89].

Recent studies have proposed AI-IoT architectures that may support more decentralized and adaptive forms of supply chain coordination. To address the complexities of coordinating dispersed stakeholders in the logistics of bulk components for modular construction, the novel Agentic AIoT framework leverages multi-agent reinforcement learning and underlying IoT infrastructure to enable autonomous scheduling adjustments in response to stochastic disruptions [25]. Furthermore, by using spatiotemporal data collected through multi-sensor IoT systems, hybrid AI models can establish real-time correlations between logistical movements and structural-component integrity. These correlations can support proactive supply chain maintenance and quality-related early warning [54].

The integration of AI and ERP systems can help establish a closed-loop digital ecosystem that bridges the gap between top-level strategic decision-making and on-site operational execution. By leveraging compact large language models and model context protocols, multi-agent systems can be embedded within ERP workflows to improve communication between AI agents and human stakeholders. This integrated architecture was designed to support automation across several stages of the reinforced-concrete component workflow, including design verification, material-specification review, production-order triggering, and shipment-logistics tracking. By improving the alignment between information flows and physical material flows, this approach provides a useful reference for the closed-loop integration of internal and external business processes within construction enterprises [47].

In summary, integrating AI with broader digital technologies may support a more integrated operational model for construction supply chains. This technological convergence may help address practical limitations such as fragmented coordination, insufficient trust, and high operating costs, while supporting a transition from experience-based methods toward more data-driven, real-time, and collaborative management.

4. Research Gaps and Future Research Agenda

Through scientometric analysis and qualitative content synthesis, this study identifies five interrelated priorities for future research on AI-enabled construction supply chains: data and interoperability; human, organizational, and practical implementation;

environmental sustainability; economic and lifecycle value; and ethics and governance. These dimensions underpin the phased research agenda shown in Figure 8 and Table 6. Although presented sequentially, issues such as ethics, cybersecurity, human oversight, and environmental measurement should be considered from the outset.

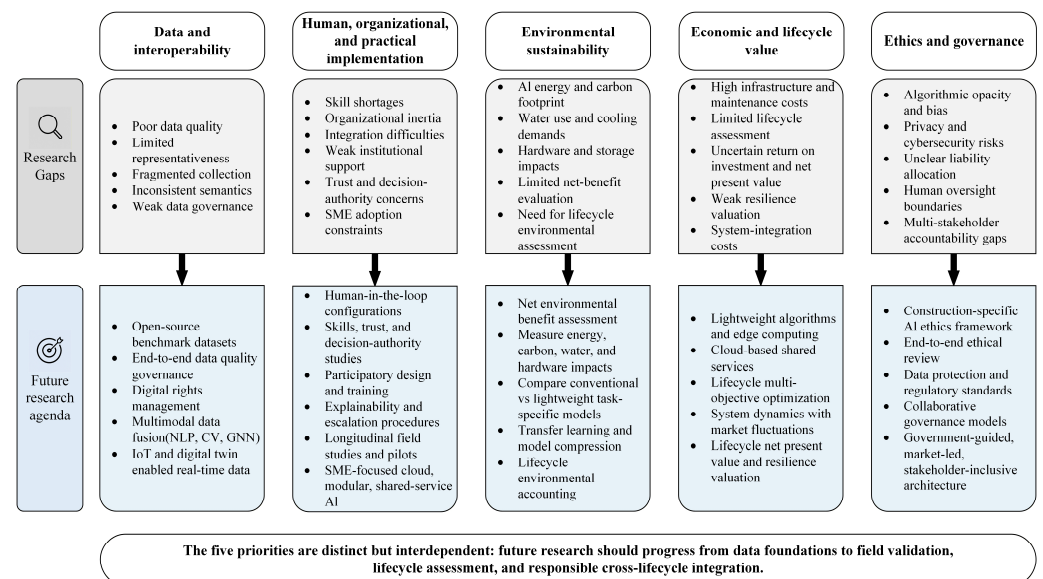


Figure 8. Research gaps and future directions of AI in construction supply chains.

Table 6. Prioritized future research agenda for AI-enabled construction supply chains.

Priority	Research Focus	Key Research Question	Expected Outcome
1. Data and interoperability foundations	Benchmark datasets, data quality, semantic consistency, and AI-BIM/ERP/IoT interoperability	How can reliable and reusable data foundations be established across projects, firms, and platforms?	Shared datasets, data-quality protocols, common taxonomies, and interoperability standards
2. Real-world validation and transferability	Field deployment, cross-project applicability, and comparison with conventional practices	Under what conditions do AI applications remain effective across projects, firms, and regions?	Empirical evidence, boundary conditions, and transferable implementation guidelines
3. Human and organizational adoption	Skills, trust, decision authority, organizational change, and SME constraints	How do human, organizational, and firm-size factors influence AI adoption and performance?	Human-centered implementation frameworks, training models, and differentiated adoption pathways
4. Lifecycle value and sustainability	Lifecycle cost, resilience, operational benefits, and AI's environmental footprint	Do the operational benefits of AI exceed its financial, energy, carbon, and resource costs?	Lifecycle evaluation frameworks and net-sustainability assessment criteria
5. Responsible cross-lifecycle integration	Explainability, cybersecurity, liability, governance, and multi-stakeholder coordination	How can AI be integrated responsibly across organizational and lifecycle boundaries?	Governance protocols, accountability frameworks, and integrated decision-support systems

For data and interoperability, future research should address poor data quality, limited representativeness, fragmented collection, inconsistent semantic structures, and weak data-governance mechanisms. Priorities include developing large-scale open-source benchmark datasets, end-to-end data quality governance, digital rights management, and multimodal processing using natural language processing, computer vision, and graph neural networks. Integration with IoT and digital twin architectures may further enable continuous, real-time data collection.

From human, organizational, and practical perspectives, AI adoption is constrained by skill shortages, organizational inertia, system-integration difficulties, weak institutional support, and resistance related to job security, professional autonomy, and decision authority. Future research should adopt a socio-technical perspective and examine how AI

interacts with human expertise, organizational structures, work practices, and institutional arrangements. Particular attention should be given to human-in-the-loop configurations, workforce skills, trust, decision authority, participatory system design, training, explainability, and escalation procedures. Longitudinal field studies and real-world pilots are needed to assess how AI reshapes roles, accountability, communication, and inter-organizational coordination. Research should also distinguish between large organizations and SMEs and evaluate low-cost, cloud-based, modular, and shared-service AI solutions for SMEs.

From an environmental perspective, studies should evaluate both the sustainability benefits enabled by AI and the lifecycle footprint of AI systems. Energy use, carbon emissions, water consumption, data storage, cooling infrastructure, and hardware production should be assessed alongside reductions in transportation emissions, material consumption, and construction waste. Comparative studies of conventional models, smaller task-specific models, transfer-learning approaches, and model-compression techniques are needed to identify solutions with the greatest net environmental benefit.

From the perspective of economic and lifecycle value, future research should determine whether gains in efficiency, resilience, and sustainability justify infrastructure, maintenance, personnel, energy, and system-integration costs. Lifecycle assessments remain limited, particularly regarding resilience, low-carbon value, and return on investment. Research should therefore explore algorithmic lightweighting, edge computing, cloud-based shared services, lifecycle multi-objective collaborative optimization, and system dynamics models that incorporate market fluctuations and lifecycle net present value.

From the perspective of ethics and governance, future research should address algorithmic opacity, bias, privacy, cybersecurity, liability allocation, human oversight, and multi-stakeholder accountability. This requires construction-specific AI ethical frameworks, end-to-end ethical reviews, data protection mechanisms, regulatory standards, and collaborative governance models. A government-guided, market-led, and stakeholder-inclusive governance architecture may provide the institutional support needed for responsible and sustainable AI implementation.

These five dimensions are distinct but interdependent. Data quality and interoperability support reliable AI development; human and organizational readiness determine adoption; environmental and economic evaluations establish lifecycle value; and ethics and governance define responsible deployment. Future research should therefore progress from foundational data development to field validation, lifecycle assessment, and responsible cross-lifecycle integration.

5. Conclusions and Implications

This study shows that research on AI-enabled construction supply chains has moved beyond isolated discussions of digital technology adoption, but the field remains unevenly developed. Evidence is strongest for task-level applications, including demand forecasting, resource optimization, logistics scheduling, material monitoring, contract and document processing, and computer vision-based inspection. Although these applications have shown potential to improve prediction, optimization, monitoring, and information processing, research on cross-organizational data sharing, governance, liability allocation, stakeholder trust, human–AI collaboration, and real-world implementation remains limited. Thus, AI's supply-chain-level value depends on data infrastructure, organizational readiness, governance mechanisms, and empirical validation.

The scientometric results show that the field is mainly organized around optimization, machine learning, sustainability, prefabrication, digital integration, and computer vision. Prediction and optimization research is comparatively mature, whereas links with contractual governance, inter-organizational coordination, resilience, and lifecycle accountability

remain weak. Future studies should therefore examine how AI-generated insights are translated into coordinated actions among owners, contractors, suppliers, logistics providers, and regulators.

Organizations should adopt AI through a phased, data-centric strategy. Early-stage adoption may prioritize applications with accessible data and clear operational value, such as procurement forecasting, supplier evaluation, contract extraction, inventory monitoring, logistics scheduling, and risk early warning. Intermediate-stage adoption may integrate AI with BIM, ERP, IoT, digital twins, smart contracts, and multi-agent systems where data compatibility, model quality, information-exchange protocols, and stakeholder responsibilities are established. Advanced-stage adoption should develop governance mechanisms for explainability, data ownership, cybersecurity, liability allocation, and human oversight. Large organizations may invest in integrated platforms and in-house capabilities, whereas SMEs may benefit from modular, cloud-based, and lower-cost solutions.

From a policy and industry perspective, wider AI diffusion requires shared data standards, open benchmark datasets, task-classification frameworks, affordable training, and financing support, particularly for SMEs. AI-BIM implementation also requires shared semantic definitions, model-validation requirements, version-control procedures, and clear rules for access to and responsibility for BIM-derived data. Sustainability assessments should further consider the computational and infrastructure footprint of AI and prioritize applications whose lifecycle benefits exceed their energy, carbon, and resource costs.

Several limitations should be acknowledged. First, the review relied mainly on English-language, peer-reviewed journal articles indexed in Scopus, which may underrepresent non-English studies, industry reports, technical standards, conference proceedings, and practice-oriented evidence. Consequently, the identified clusters should be interpreted as a map of the Scopus-indexed literature rather than a complete representation of the entire knowledge domain. Future reviews could integrate Web of Science, Engineering Village, IEEE Xplore, ACM Digital Library, ASCE Library, and relevant conference proceedings.

Second, the dataset covered publications indexed up to April 2026. Rapidly emerging topics, including generative AI, large language models, autonomous agents, AIoT, and digital twin-based decision systems, may therefore be underrepresented. Terms such as “generative AI,” “LLMs,” “GPT-based systems,” and “foundation models” were not standalone primary search terms, although relevant studies retrieved through broader AI terms were included. Future reviews should update the search and explicitly incorporate emerging terminology.

Third, scientometric results depend on occurrence and citation thresholds, the full-counting method, and thesaurus standardization. Citation indicators may favor older publications, while co-occurrence and co-citation relationships indicate intellectual association rather than research quality, practical effectiveness, or causality. These findings should therefore be interpreted together with the qualitative synthesis.

Fourth, qualitative content synthesis involves interpretive judgment. Although an explicit coding framework, independent pilot coding, category refinement, and consensus-based resolution were used, researcher subjectivity cannot be eliminated. Future studies could publish coding datasets, apply formal inter-coder reliability measures, and test alternative classification schemes.

Fifth, the human consequences of AI adoption remain underexplored. Evidence on workforce acceptance, job redesign, decision authority, trust, professional autonomy, and human–AI collaboration is limited and uneven across organizational, project, and supply chain contexts. Therefore, this review identifies the human dimension as an important research gap but cannot draw definitive conclusions about AI’s effects on workers, professional roles, decision authority, or organizational performance.

Finally, the heterogeneous evidence base prevents a quantitative estimate of AI's overall effect on construction supply chain performance. Many studies remain simulation-based, prototype-based, or project-specific, with limited longitudinal and cross-project evidence. Future research should use longitudinal field studies, multi-project comparisons, experiments, and mixed-method approaches to examine transferability, boundary conditions, differences between SMEs and large organizations, and long-term performance.

Overall, these limitations define the scope of the findings rather than invalidate them. This study provides a structured synthesis of Scopus-indexed evidence, while its research agenda should be refined as broader databases, emerging technologies, and stronger real-world evidence become available.

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