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AI Applications in Project-Based Supply Chain Coordination and Risk Governance

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Abstract:

The increasing complexity of construction projects has underscored persistent challenges in supply chain coordination and risk governance. Traditional management tools often fail to address fragmented communication, information silos, and limited predictive capacity in risk identification. Large language models (LLMs), with their advanced natural language processing and reasoning capabilities, offer a transformative potential to enhance collaboration and adaptive governance in such contexts. This paper conducts a systematic literature review of recent studies across IEEE, Springer, Elsevier, and arXiv, classifying existing research by application scenario, methodology, and outcomes. The findings reveal that LLMs are most effective in improving communication and standardizing information exchange, while their application to predictive risk governance remains largely conceptual and underexplored. This highlights an important disparity between the predictive and assistive capabilities of Large Language Models (LLMs) in this area. Integrating digital platforms, for example, Building Information Modeling (BIM) and blockchain technology, is suggested as an eventual enabler of building the resilience and openness of supply chains. Nonetheless, the review presents significant gaps, for example, the lack of domain-specific fine-tuning, the lack of empirical verification in construction contexts, and the less-than-adequate integration from coordination- and governance-based viewpoints. The paper concludes by positing that LLMs should serve as collaborative infrastructures in supply chains best as they are optimally accessed using hybrid governance structures infusing artificial intelligence-based processes and blockchain as well as statistical procedures. Future work should focus on empirical case studies, system integration, and capacity building for closing the gap between potential applications on paper and practical application.

Keywords: Construction Supply Chain; Project-Based Coordination; Risk Governance; Large Language Models (LLMs); Building Information Modeling (BIM)

1. Introduction

1.1 Problem Statement

The increasing complexity of construction projects and their associated supply chains has highlighted persistent challenges in coordination, communication, and risk governance. Standard project management methods consistently face challenges in the form of fragmented data exchanges, inefficient inter-stakeholder collaborations, and limited capacity for predictive risk [1]. In large, multi-stakeholder construction projects, where timely integration of data and decision-making among contractors, suppliers, and regulatory agencies are crucial, recent advances in large language models (LLMs) offer an innovative and effective solution. LLMs, featuring their ability in natural language manipulation as well as knowledge integration, have been utilized in lean construction [2] as well as in multi-agent systems [3] for supporting decisions. Nonetheless, their application in the coordination of project-based supply chains lacks thorough exploration. In the existing literature, there has not been an exhaustive exploration on how LLMs may improve cross-functional communication, strengthen risk governance mechanisms, as well as provide flexible solutions for supply chain disruptions [4]. In addition, available digital tools in construction tend to reside within isolated data silos without the ability for semantic understanding as well as reasoning inherent in LLMs, handicapping their performance in the management of complex interdependencies at different supply chain tiers [5]. LLMs may act as intelligent cognitive brokers where stakeholders' objectives may be aligned, as well as contractual documents as well as risk patterns may be interpreted upon the extraction of unstructured communication data [6]. In this respect, the study aims at filling the literature gap by synthesizing recent applications of LLMs in relevant areas as well as exploring their promise for transforming inter-stakeholder collaborations in the construction supply chain. Specifically, the study assumes heightened relevance for post-pandemic situations where the digital resilience as well as agile mechanisms for reactions turned into strategic imperatives for infrastructure development [7]. In this way, it seeks to develop a conceptual framework linking AI-oriented knowledge management to effective governance strategies as both providing theoretical advancement as well as practical application.

1.2 Literature Status and Research Gaps

Despite substantial growth in AI research for supply chain and project management, the integration of Large Language Models (LLMs) into construction-specific contexts remains nascent. In the broader supply chain literature, AI applications have demonstrated value in predictive analytics, logistics optimization, and decision-making under uncertainty [8]. Studies on generative AI in construction highlight opportunities for process automation and knowledge reuse, particularly in lean project delivery systems [9]. Similarly, LLM-enhanced frameworks have been investigated for improving multi-model programming environments and collaborative data systems [10]. Despite these advances, much of the current research is either theoretical or confined to non-construction domains, such as financial technology or general agentic AI systems [11,12]. However, when narrowing the focus to the specific application of LLMs in construction supply chain coordination and risk governance, the literature reveals significant limitations. Within the construction management field, attention has been directed toward blockchain-enabled transparency and digitalization, but systematic explorations of how LLMs can directly support project-based coordination and risk governance are limited [1]. The literature also reveals a lack of empirical studies addressing real-world construction case applications, which restricts the transferability of theoretical insights into practice. This gap underscores the need for targeted investigations into LLM-driven collaboration mechanisms, particularly in addressing fragmented communication, risk anticipation, and adaptive decision-making across supply chain networks.

Furthermore, although LLMs have shown strong capabilities in information retrieval and semantic reasoning, current implementations in construction tend to be isolated pilot studies with limited scalability. Many platforms have integrated basic natural language processing capabilities; they don't exploit the generative and contextual advantage of transformer-based architectures, such as GPT-4 or Claude 2. It may partly be due to sector-specific challenges, including project uniqueness, varying regulative regimes, as well as stagnation in the area of digital evolution among subcontractors [13]. In cases where large language models are utilized, they mostly serve in ancillary roles, conducting activities such as document summarization or question-answering aids, but not being comprehensively integrated into the coordination processes or risk management workflows.

Furthermore, industry reports in the past year also showed that another main adoption barrier is the absence of field-specific training data for construction-related LLM applications, hindering their accuracy and situational understanding in the intricate field situations [14]. Though in companies where pilot applications of LLMs have been tried, integration challenges within old software systems as well as middle management resistance delayed all-scale application. Such hesitance was aggravated by the non-uniform digital infrastructure between regions as well as companies, resulting in patchy technology readiness as

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well as exacerbated gaps in AI-capable coordination capacity [15].

Recent trends suggest the promise of augmenting LLMs using digital twins as well as online IoT data for predictive governance mechanisms but as yet only remain speculatory and devoid of solid empirical verification. There also continues skepticism about model alignment, human-in-the-loop explainability, as well as control required in high-risk, multi-party project situations like construction. Therefore, for LLMs to transition from novelty to necessity in the built environment, future research must focus on scalable, cross-platform integration methods that accommodate the fragmented and dynamic nature of construction supply chains.

2. Research Design and Methodology

Following the proposed research design, this study adopts a systematic literature review to classify and compare how large language models (LLMs) have been explored in project-based supply chain coordination and risk governance. The research is guided by three interrelated questions:

(1) How can LLMs improve collaboration and information flow among construction project stakeholders?

(2) In what ways can LLMs contribute to risk governance in dynamic supply chain environments?

(3) What are the limitations and research gaps that remain unresolved?

To answer these, the literature was screened from leading databases, including IEEE Xplore, SpringerLink, Elsevier, and arXiv. The sources were classified according to application scenarios, methodological approaches, and evaluation outcomes. Comparative analysis was then conducted to distill common themes, divergences, and emerging research trends. This rigorous methodological sequence was designed to ensure the validity and reliability of the findings, aligning with the problem-driven nature of this study.

The selection criteria emphasized peer-reviewed journal articles and conference proceedings published between 2020 and 2025, with explicit focus on either LLM applications or AI-supported coordination in the construction industry. Papers addressing adjacent domains such as manufacturing, logistics, and digital governance were included selectively, provided they offered transferable insights to the project-based construction context. Initial keyword queries included combinations such as “large language model + supply chain,” “AI + construction risk,” and “GPT + collaboration,” and were refined iteratively to increase relevance and coverage [16].

Over 80 papers were initially retrieved, and a final set of 25 high-relevance publications was subjected to thematic coding and cross-comparative mapping. A structured coding framework was developed, analyzing the final corpus along three primary dimensions: (a) the domain of application (coordination, risk, or hybrid); (b) the primary LLM functionality (e.g., summarization, Q&A, anomaly detection); and (c) the implementation readiness (conceptual, prototype, or deployed). NVivo was used to support qualitative synthesis and trace conceptual patterns across studies [17].

By using this rigorous methodology, the review avoids anecdotal or overly generic claims and instead builds on structured evidence to support the analysis presented in subsequent sections.

3. Result: Research Findings

3.1 LLMs Enhance Coordination through Improved Communication

The analysis of the literature reveals distinct themes regarding the application of LLMs. Regarding supply chain coordination, the literature indicates that the application of LLMs has been most prominently explored for enhancing coordination mechanisms. For example, Rad and Ilbeigi highlight the role of generative AI in lean construction, showing its utility in automating design reviews and standardizing communication protocols [2]. Similarly, Wang et al. present the CAMP framework, which integrates LLMs in local-cloud co-pilot systems, emphasizing efficiency in multi-model collaboration [10]. Across these studies, the common contribution lies in reducing communication bottlenecks and ensuring consistency of shared information. However, a key challenge identified is the lack of domain-specific fine-tuning, which results in generic LLMs often failing to interpret construction-specific terminology with sufficient precision.

Specifically, construction project coordination involves frequent RFIs (Requests for Information), submittals, and meeting minutes using frequently ambiguous language or project-specific slang. Trained on little data of this type, the general-purpose LLMs might misunderstand technical details or not disambiguate context-dependent meaning properly, leading to miscommunications or delays. Rad and Ilbeigi’s investigation also highlights the value of prompt-engineering strategies for construction dialogue flows specially designed for LLMs to capture the logic of co-design review meetings more accurately [2].

Wang et al.’s CAMP also highlights the promise of integrating LLMs with building information platforms such as BIM to improve semantic interoperability among stakeholders [10]. Through the translation of abstract model attributes into human-accessible abstracts, LLMs may alleviate inter-engineer knowledge gaps as well as those between contractors and administrative personnel, promoting mutual understanding without misinterpretations. Additionally, the applications hold promise for permitting coordination over different languages, the primary issue in overseas projects.

Nonetheless, despite these innovations, the transition from experimental prototypes to deployed systems remains limited. There is a need for validated benchmarks that evaluate coordination performance improvements, as current evidence is largely conceptual or based on simulation environments. Practical applications should also consider integration with existing communication software used on job sites, such as Procore or Navisworks, to enhance adoption feasibility.

3.2 Emerging but Limited Applications in Predictive Risk Governance

In contrast to the coordination-focused applications, the role of LLMs in risk governance is less developed but shows potential. The review indicates that risk management has been a secondary but emerging area of LLM applications. Núñez-Chongo et al. demonstrate how data-driven workflows can be structured to detect early warning signals in high-risk environments [8]. By extension, such methods suggest that LLMs could be applied to construction supply chains to detect supplier reliability issues, contractual ambiguities, or potential delays. Harty, although focusing on blockchain, provides evidence of the importance of transparent and accountable supply chains [1]. It suggests thus the potential for an interlinking of blockchain ledgers with LLM-based analysis to develop a stronger risk governance regime. In the literature review, however, few empirical studies directly on construction-specific risk forecasting appear as evidence, justifying additional applied case studies.

One of the major areas where LLMs could aid risk governance involves the analysis of unstructured data, for example, incident reports, safety audits, and legal documents, which tend not to be utilized fully in today's risk assessment processes. Processing the text-laden inputs, LLMs could provide actionable summaries or risk flags highlighting non-obvious patterns of failure or non-compliance among projects. For example, recurrent references to rework orders in the correspondence of subcontractors could provide an indicator of underlying quality or coordination problems before project-wide disruptions occur.

In addition, LLMs may aid contract interpretation as well as semantic comparison of clauses between suppliers or jurisdictions where the alignment or clarity may lead to legal controversy. In the high-risk, multi-party contracts characteristic of infrastructure megaprojects, this ability for comparative language processing provides an additional dimension of early-stage risk management. Deployed as an ingredient within supply chain dashboards, the models might provide real-time access into dynamic risk profile changes dependent upon shifting documentation as well as communication dynamics.

Yet applications today proceed largely as speculation or in early pilot phases without in-the-field verification. Scant few available papers utilize longitudinal data or before-after designs for the purpose of ascertaining the effect of LLM-based interventions on risk measures such as delay frequency, safety events, or claims. Consequently, the current literature underscores a pressing need for developing measurable frameworks and conducting longitudinal field trials within live construction projects to move beyond hypothetical applications.

3.3 Identified Research Gaps and Implementation Barriers

Despite promising insights, the literature review shows that existing studies remain fragmented. Talukdar et al. explore agentic AI systems for multi-agent collaboration, but their applications are mostly theoretical or tested in controlled environments rather than real construction projects [12]. This disconnect between simulation and field deployment limits the generalizability of findings, particularly in the context of complex, multi-stakeholder construction supply chains where operational unpredictability is high. Scenarios used in academic trials often assume clean, structured data and well-defined workflows, which do not reflect the fragmented communication and inconsistent documentation commonly found on real job sites.

Shi et al. present a multi-agent LLM framework for pest management, which—though outside the construction domain—illustrates cross-sectoral potential [11]. However, such transpositions require careful consideration of contextual variables unique to the built environment, including physical site constraints, regulatory heterogeneity, and contractual fragmentation. There is little evidence that LLM-based agents have been trained or fine-tuned using construction-specific datasets, raising concerns about semantic misinterpretation and decision quality when models are deployed in domain-specific use cases.

Another notable limitation is the lack of systems thinking in most reviewed studies. LLMs are often evaluated in isolation, without assessing how their outputs affect upstream planning or downstream execution decisions. For example, a model may flag coordination issues, but whether this flag triggers reallocation of resources or change orders is rarely discussed or tested. The absence of longitudinal studies, limited cross-validation, and the lack of integration between coordination and governance frameworks all represent pressing gaps.

Collectively, these limitations can be synthesized into three overarching gaps that hinder the advancement of

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LLMs in this field: (1) a methodological gap, characterized by a predominance of conceptual or simulated studies lacking real-world validation; (2) a technical gap, involving insufficient domain adaptation and a lack of systems-level integration; and (3) a socio-technical gap, pertaining to the neglect of organizational, cultural, and human factors in implementation.

Furthermore, studies seldom address the organizational or cultural barriers to adopting LLMs in conservative construction settings, where digital transformation remains uneven. Factors such as workforce training, liability allocation, and trust in AI recommendations are rarely examined, yet they are critical to real-world implementation. Without addressing these human-institutional dimensions, the promise of LLMs risks being confined to proof-of-concept exercises rather than becoming an operational norm in project-based supply chains.

4. Discussion

4.1 Process of Interpretation

The findings reveal that while LLMs are frequently positioned as coordination tools, their potential as governance instruments is less systematically studied. This aligns with the first research question: LLMs can indeed improve collaboration by acting as intermediaries of information exchange, but their effectiveness depends on customization and contextual adaptation. This disparity suggests that the field currently prioritizes LLMs' utility in overcoming immediate, operational communication barriers, while their strategic role in anticipatory risk control—which requires higher model reliability and integration—is yet to be fully embraced. More specifically, the reviewed studies show that the success of LLM deployment is often tied to their ability to process localized terminologies, interface with construction-specific workflows, and adapt to regulatory variations across regions. Off-the-shelf models may offer initial insights but lack the nuance required for domain-specific reasoning and structured coordination.

Conversely, the application of LLMs to risk governance remains markedly tentative and predominantly tentative. The reviewed studies provide indirect evidence that LLMs could support predictive governance, but the application is still largely speculative. While some pilot frameworks suggest that anomaly detection and pattern recognition could be embedded within LLM architectures to monitor supplier behavior or contractual inconsistencies, no study has demonstrated these features in a full-cycle construction project. The construction industry lags behind other domains, such as logistics and manufacturing, in operationalizing AI-driven risk identification. This reflects structural barriers such as heterogeneous data formats, contractual sensitivity, and a cautious adoption culture. The sensitivity of construction documents—particularly regarding cost variations, liability structures, and subcontractor performance—complicates the use of LLMs as autonomous or semi-autonomous governance agents. As a result, firms remain hesitant to delegate high-stakes decision-making to models that are not fully transparent or explainable.

The process of comparative analysis also clarifies a methodological point: most reviewed studies use conceptual frameworks or prototype systems, rather than empirical evaluation in live projects. This reinforces the observation that the field is still in an exploratory phase, where theorization outpaces field validation. Only a minority of works link AI interventions to measurable outcomes such as delay reductions, cost savings, or communication efficiency gains. This indicates a critical methodological chasm between recognizing the potential of LLMs and executing research designs that are capable of validating their impact within the messy, real-world contexts of construction projects. An implication of this is the pressing need for cross-disciplinary collaborations between AI developers, construction engineers, and project managers to co-develop testable, scalable systems. Thus, the contribution of this review is not only to highlight current uses but also to expose the methodological immaturity in this research stream.

In direct response to the research questions, this discussion clarifies that: (1) LLMs improve collaboration primarily by standardizing information exchange, but their efficacy is contingent on domain-specific adaptation; (2) their contribution to risk governance is currently hypothetical, pointing to a high-potential but high-stakes research frontier; and (3) the most significant limitations are the methodological and socio-technical gaps identified, which prior reviews have not systematically articulated. Thereby, this study moves beyond cataloging applications to providing a critical framework for diagnosing the field's maturity and directing its future evolution.

4.2 Research Contributions and Viewpoints

Synthesizing the findings, this review contends that the path to leveraging LLMs in construction supply chains lies not in pursuing isolated applications, but in fostering a paradigm shift towards integrated, intelligent governance ecosystems. This central argument is supported by three pivotal viewpoints:

4.2.1 LLMs as collaborative infrastructure

The analysis indicates that LLMs are most effectively conceptualized not as add-on tools, but as collaborative infrastructure within project supply chains. They are most effective when embedded into digital ecosystems such as BIM or blockchain, ensuring integration rather than parallel deployment.

This integration allows LLMs to act as connective agents that interface between disparate information silos—translating model data into contract language, stakeholder feedback into structured updates, and system alerts into actionable summaries. By embedding LLMs within the design–build–operate lifecycle, construction firms can unlock real-time collaboration, continuous knowledge reuse, and cross-disciplinary visibility that current tools fail to deliver. In such a role, LLMs are not merely "assistive agents" but become infrastructural mediators shaping project flow.

4.2.2 Risk governance requires hybrid systems

A single AI model is insufficient for risk governance. Future work should explore hybrid systems where LLMs provide textual interpretation and predictive reasoning, while blockchain and statistical models secure traceability and quantitative validation [1,8].

This reflects a broader systems-thinking approach where governance is not the result of one model's prediction but of synergistic mechanisms working in parallel. LLMs may process and flag semantic inconsistencies in legal clauses or emails, while blockchain ensures immutability of reporting logs, and sensor-based models offer real-time metrics. Combining probabilistic risk scoring with contextual understanding enables more robust early warning systems. Importantly, hybrid architectures can support varying levels of autonomy, offering human-in-the-loop control where required, which is essential for high-stakes project environments.

4.2.3 Bridging concept and practice

The gap between theoretical designs and empirical validation is the most pressing issue. Subsequent phases of the work should develop from speculative theory to rigorously-methodological case studies on genuinely-in-progress construction projects yielding practical evidence amenable for scholars as well as for practitioners.

While theoretical work provides much for hypothesis development, over-reliance has led to applied testing stagnation. In the absence of longitudinal case studies or sandboxed pilot implementations, it's challenging to test whether LLM-facilitated systems actually minimize project overruns, improve safety, or facilitate coordination under uncertainty. Researchers need to work jointly with companies to co-design research protocols incorporating both scientific validity and operational applicability.

These viewpoints reflect the process of interpretation: starting from literature classification, identifying consistent findings, confronting observed gaps, and formulating constructive pathways forward.

5. Conclusion

In conclusion, this systematic review establishes that Large Language Models (LLMs) possess considerable potential to address long-standing challenges in construction supply chain coordination and risk governance. The literature indicates that their strongest contributions lie in enhancing multi-stakeholder communication and offering potential for predictive insights in risk management. Their ability to process large volumes of unstructured textual data positions them as ideal tools for navigating the complexity and fragmentation typical of construction environments. However, this review also reveals a body of research that is currently fragmented, methodologically immature, and lacking in empirical validation. In particular, few studies provide quantifiable results linking LLM deployment to improvements in cost, time, or safety performance. The principal contribution of this review lies in systematically mapping this terrain, synthesizing a fragmented field, and distilling the key conceptual and practical impediments that must be overcome to realize the potential of LLMs.

To advance this field, future research should adopt the following pathways:

Empirical Validation: Conduct pilot implementations in real-world construction projects to measure the impact of LLMs on coordination efficiency and risk mitigation. This requires longitudinal tracking of AI-enabled workflows and comparison against baseline project performance metrics to determine added value.

System Integration: Explore how LLMs can be embedded within existing digital infrastructures such as BIM and blockchain to ensure interoperability. Such integration should also consider how LLMs interface with common construction software tools and data standards, ensuring scalability across firm sizes and project types.

Governance Frameworks: Develop hybrid models combining AI, blockchain, and traditional supply chain governance mechanisms to ensure both predictive capability and transparency. A multi-layered governance system can enhance trust, especially when AI decisions are traceable, explainable, and auditable.

Capacity Building: Train construction professionals in the use of AI tools, fostering both technical literacy and organizational readiness. Workforce development is essential to ensure that LLM applications are not merely available but actively used in daily project routines.

By aligning AI innovation with construction-specific needs, this review argues that LLMs should be understood not merely as tools but as catalysts for a paradigm shift in project delivery. They can contribute not only to more efficient coordination but also to more resilient and adaptive governance in project-based supply chains. Ultimately, their strategic value lies in enabling informed

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decision-making, reducing information asymmetry, and fostering a culture of proactive risk anticipation.

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