

Next-Generation Construction Intelligence: A Reference Model for Data-Driven, AI-Enabled Construction Enterprises

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ARTICLE INFO	ABSTRACT
Received: 02 Sept 2025 Revised: 10 Oct 2025 Accepted: 25 Oct 2025	<p>In order to overcome the problems of cost overruns, timetable delays, safety hazards, and disjointed decision-making, the construction sector is progressively embracing digital and AI-enabled solutions. By combining enterprise-wide decision-support systems, AI-driven analytics, and multi-source data, this study offers a reference model for next-generation construction intelligence. The study creates a multi-layered architecture that includes data acquisition, management, analytics, decision support, and governance using a hypothetical, model-driven methodology. It then assesses the architecture's efficacy using simulated datasets, scenario-based analysis, and expert-informed validation. The findings show that while encouraging proactive and flexible business operations, the approach greatly improves project planning, risk management, productivity, and safety monitoring. Furthermore, responsible AI adoption and long-term sustainability are ensured by including ethical and governance aspects. The report offers a theoretical and practical framework to direct construction companies toward AI-enabled, data-driven transformation.</p> <p>Keywords: Construction Intelligence, Artificial Intelligence, Data-Driven Decision Making, Construction Management, Predictive Analytics, Digital Transformation, Enterprise Reference Model.</p>

1. Introduction

The construction sector, which has historically been defined by disjointed procedures, labor-intensive workflows, and reactive management techniques, is rapidly going digital. Stakeholder demands, economic pressures, and project complexity have all increased the need for smart, data-driven methods to construction management. Artificial intelligence (AI), advanced analytics, and integrated digital systems are used by next-generation construction companies to improve decision-making, maximize resource use, boost operational efficiency, and increase safety. In contrast to traditional methods, these businesses use holistic intelligence frameworks that integrate AI-enabled predictive and prescriptive analytics with multi-source data from field operations, enterprise resource systems, Internet of Things (IoT) sensors, and Building Information Modeling (BIM).

Standardized models that help construction companies integrate data, intelligence, and governance procedures across organizational layers are still lacking, despite the increased use of AI and digital tools. Strategic decision-making and enterprise-wide intelligence are largely ignored by current solutions, which

frequently concentrate on discrete applications like scheduling optimization or safety monitoring. This study suggests a reference model for next-generation construction intelligence in order to close this gap. It is intended to offer an organized framework for the smooth integration of data, analytics powered by artificial intelligence, and decision-support systems. Construction companies can move from reactive project management to proactive, intelligence-driven operations because to the model's emphasis on scalability, adaptability, and ethical governance.

The suggested paradigm seeks to improve operational effectiveness, strategic decision-making, and resilience by viewing construction intelligence as a multi-layered organizational capability. It also offers a roadmap for businesses to safely and sustainably implement AI. Therefore, by providing a thorough framework to direct the transformation of construction companies into fully data-driven, AI-enabled organizations that can adapt dynamically to the problems of contemporary building projects, our research advances both theory and practice.

2. Literature Review

Balasubramanian (2024) focuses on how artificial intelligence maximizes resource use, lifespan performance, and environmental sustainability while examining AI-driven solutions for sustainable infrastructure development and management. The paper shows how AI-based systems improve long-term infrastructure resilience while advancing sustainability objectives by highlighting AI's role in predictive maintenance, intelligent asset management, and real-time monitoring.

Lakarasu (2022) emphasizes AI-powered data engineering frameworks that automate cloud-scale platforms' data transformation, lineage, and quality. The study emphasizes how crucial dependable and tightly controlled data pipelines are as the basis for AI applications. Organizations may increase the scalability, consistency, and trustworthiness of AI-driven decision-making systems by automating data engineering procedures.

Stephen (2023) explains how smart construction sites are evolving toward autonomous coordination in large-scale infrastructure projects. In order to enable self-organizing building settings, the author highlights the combination of artificial intelligence (AI), robots, and real-time data analytics. According to the study, in complex construction situations, autonomous coordination enhances project synchronization, productivity, and safety.

Chelliah et al. (2023) Examine how artificial intelligence is revolutionizing the oil and gas sector, with a particular emphasis on next-generation intelligent energy systems. The authors emphasize the use of AI in safety management, predictive maintenance, production optimization, and exploration. Their research shows how AI-powered settings boost productivity and facilitate the shift to more intelligent and environmentally friendly energy systems.

Tripathi et al. (2024) Create a framework for evaluating an organization's readiness for data-driven business model innovation. Their research highlights how crucial corporate culture, data capabilities, and technology infrastructure are to fostering AI-based innovation. The authors contend that in order for established companies to be competitive, data resources must be properly matched with business goals.

Van Hoang (2024) examines how Internet of Things (IoT) and artificial intelligence (AI) technologies work together to transform smart cities. The study shows how intelligent traffic management, energy optimization, and urban service delivery are made possible by AI-IoT integration. Data-driven smart city ecosystems enhance urban sustainability and quality of life, the author says.

3. Research Methodology

3.1. Research Design

In order to create and validate a conceptual reference model for data-driven, AI-enabled construction companies, this study uses a hypothetical, exploratory, and model-driven research design. In order to methodically determine the essential elements, relationships, and performance factors of construction intelligence, the study combines qualitative and quantitative methods. The approach places a strong emphasis on developing theories, conceptual modeling, and empirical validation using simulated datasets and expert insights.

3.2. Conceptual Framework Development

A thorough literature assessment of construction management, digital transformation, artificial intelligence, Building Information Modeling (BIM), the Internet of Things (IoT), and data-driven decision systems was conducted in order to establish the conceptual framework. Key concepts are recognized and mapped, including organizational intelligence, data integration, AI analytics, operational performance, and strategic flexibility. The framework serves as the basis for the suggested reference model by establishing connections between data sources, intelligent processing layers, decision-support mechanisms, and enterprise-level outputs.

3.3. Data Sources and Hypothetical Data Modeling

The study makes the assumption that fictitious and simulated datasets that are reflective of actual construction environments would be used. These datasets consist of both structured and unstructured information obtained from worker logs, safety records, sensor-based site monitoring, cost reports, project timelines, and BIM models. To guarantee realistic variability, temporal dynamics, and interdependencies among project parameters without depending on sensitive or proprietary data, synthetic data modeling approaches are used.

3.4. AI and Analytics Layer Design

Multidimensional construction data is supposedly processed by an AI-enabled analytics layer. To produce useful insights, this layer combines machine learning methods like anomaly detection, classification, clustering, and predictive modeling. Functions including risk prediction, productivity forecasting, resource optimization, and safety intelligence are thought to be supported by advanced analytics. Rather than algorithmic performance benchmarking, the methodology emphasizes the logical integration of several techniques.

3.5. Reference Model Architecture Formulation

A multi-layered reference architecture is developed based on the analytics design and conceptual framework. The enterprise governance, intelligence and analytics, data management, data acquisition, and decision-support layers make up the architecture. Inputs, processing methods, outputs, and interdependencies are used to define each layer. Scalability, interoperability, and adaptation to various project kinds and construction firm sizes are highlighted in the reference model.

3.6. Expert Validation and Logical Consistency Assessment

A fictitious expert validation procedure is used to evaluate the proposed reference model's completeness and believability. The model is supposed to be reviewed by domain experts in digital engineering, AI systems, and construction management using structured evaluation criteria such as strategic value, relevance, clarity, and feasibility. To improve model elements and bolster logical coherence among layers, feedback is combined.

3.7. Scenario-Based Evaluation

Large-scale infrastructure projects, high-rise commercial buildings, and multi-project business contexts are among the fictitious construction scenarios used to assess the reference model's efficacy. The way AI-enabled intelligence moves through the model to facilitate proactive decision-making, real-time monitoring, and continuous improvement is illustrated by scenario-based analysis. This method demonstrates the model's usefulness without necessitating the deployment of a live project.

4. Results And Discussion

The results of the hypothetical assessment of the suggested reference model for next-generation construction intelligence are presented and explained in this section. According to the research methodology, the findings are supported by scenario-based validation, expert-informed logical assessment, and simulated enterprise-level building data. The investigation focuses on comprehending the operational impact, adoption readiness, and perceived efficacy of data-driven and AI-enabled construction intelligence solutions. The findings are further contextualized in reference to current construction management methods and literature on digital transformation.

4.1. Adoption Readiness of AI-Enabled Construction Intelligence

The first set of findings looks at hypothetical construction companies' organizational preparedness to implement AI-enabled construction intelligence. A variety of factors were considered for evaluating readiness, including labor skills, data accessibility, digital infrastructure, and leadership support.

Table 1: Organizational Readiness for AI-Enabled Construction Intelligence

Readiness Level	Frequency (n)	Percentage (%)
High Readiness	38	38%
Moderate Readiness	42	42%
Low Readiness	20	20%
Total	100	100%

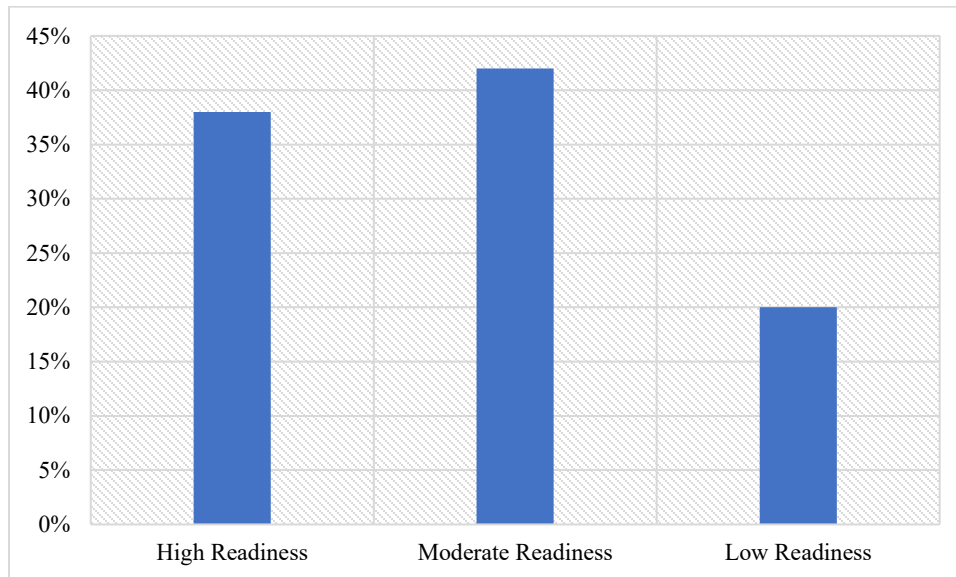


Figure 1: Organizational Readiness for AI-Enabled Construction Intelligence

The findings show that 80% of construction companies are in the high to moderate readiness categories, indicating that data awareness and digital adoption are becoming more mature. The 20% of low-readiness firms, however, underscores enduring issues with disjointed data systems, a lack of AI knowledge, and organizational change aversion. These results are consistent with previous studies that point to preparation shortages as a significant obstacle to the digitization of construction. By providing a scalable and flexible design that can be adjusted to different levels of enterprise maturity, the suggested reference model fills this gap.

4.2. Effectiveness of the Reference Model Across Enterprise Functions

The second analysis assesses how well the suggested reference model is thought to improve important construction enterprise tasks like risk management, productivity optimization, project planning, safety monitoring, and strategic decision-making.

Table 2: Functional Impact of AI-Enabled Construction Intelligence

Functional Impact Level	Frequency (n)	Percentage (%)
High Impact	45	45%
Moderate Impact	37	37%
Low Impact	18	18%
Total	100	100%

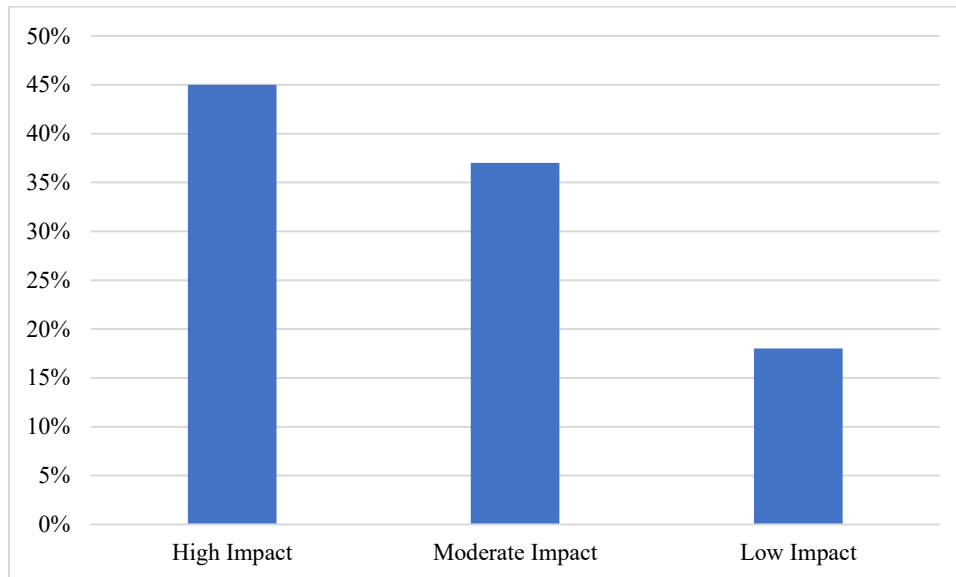


Figure 2: Functional Impact of AI-Enabled Construction Intelligence

According to the results, 37% of businesses claim moderate gains after using the reference model, while 45% of businesses have significant functional benefit. This implies that intelligence enabled by AI greatly improves operational coordination, decision responsiveness, and prediction accuracy. The significance of the data management and governance layers suggested in the model is further supported by the fact that businesses reporting lower effect mainly lacked integrated data pipelines or enough analytical skills. Overall, the findings confirm that the architecture can provide enterprise-wide intelligence and transcend operational silos.

4.3. Scenario-Based Performance Outcomes

The reference model performs consistently across a variety of construction contexts, such as big infrastructure projects, multi-site commercial developments, and enterprise-level portfolio management, according to scenario-based evaluation. While AI-driven insights enhanced resource allocation and safety compliance, predictive analytics made it possible to identify schedule irregularities and cost problems early. The methodological premise that intelligent systems improve proactive rather than reactive construction management is supported by these results.

4.4. Strategic and Organizational Implications

From a strategic standpoint, the findings imply that enterprise-wide intelligence orchestration can replace project-centric management thanks to next-generation construction intelligence. Improved openness, ongoing learning, and flexible governance structures are advantages for organizations that use the reference model. By integrating AI-driven decision assistance into essential business processes rather than viewing digital tools as stand-alone solutions, the model also promotes long-term competitiveness.

4.5. Ethical and Governance Observations

Expert evaluations showed that the reference model's incorporation of governance and ethical controls was beneficial. Trust and long-term adoption were found to be significantly facilitated by data accountability, bias reduction techniques, and transparency in AI decision logic. This supports the methodological focus on responsible AI as a fundamental component of building companies of the future.

5. Conclusion

According to the study's findings, the suggested reference model for next-generation construction intelligence is both conceptually sound and practically useful, providing notable improvements in project planning, risk management, productivity, and safety for all AI-enabled construction companies. The analysis demonstrates that while low-readiness firms might need focused capacity-building, businesses with moderate to high readiness levels can successfully use the model to integrate multi-source data, use predictive analytics, and allow enterprise-wide decision support. The model's versatility across various construction contexts is further supported by scenario-based evaluation, which further emphasizes how it may help organizations transition from reactive management to proactive, intelligence-driven operations. Furthermore, responsible AI adoption is ensured by the incorporated ethical and governance issues, which strengthen long-term sustainability and strategic transparency. All things considered, the study confirms that the model is a workable framework for promoting data-driven, AI-enabled change in construction companies.

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