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# A Critical Review and Metadata-Driven Analysis of Artificial Intelligence (AI) Applications in the Construction Industry across Project Lifecycles

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Despite a growing body of research on AI in construction, most studies remain limited in scope, concentrating on specific tools, tasks, or individual project phases. This fragmentation hinders a comprehensive understanding of AI's role throughout the entire project lifecycle. This study addresses this gap through a systematic literature review of research published between 2010 and 2024, using the PRISMA methodology. A metadata-driven analysis was conducted to facilitate deeper pattern recognition and gain a holistic understanding of AI implementation across lifecycle phases, examined through the lens of *AI techniques*, *functional roles*, *key business processes supported*, and *AI tools/models*. The findings suggest that AI is increasingly applied in the planning, design, and construction phases, while it remains underrepresented during project conception, closeout, and post-construction phases. Machine Learning (ML) dominates as the underlying AI technique, with optimization as the top functional role and risk management as the key supported business process. This study contributes to the body of knowledge by offering metadata-supported evidence and practical value for both academics and practitioners, highlighting not only what has been achieved so far but also where future efforts should be directed to promote more connected and intelligent project delivery.

**Keywords:** Artificial intelligence, Metadata, Project lifecycle, Mapping, Benchmark

## Introduction

Artificial intelligence (AI) has recently emerged as a promising solution with the potential to transform the way construction projects are conceived, designed, executed, and managed. Advances in data analytics, machine learning, computer vision, and natural language processing have broadened the scope of AI applications in construction across areas such as safety monitoring, project scheduling, cost estimation, procurement planning, and structural health diagnostics (Poh et al., 2018; Hatami et al., 2022; Shibu et al., 2023). These developments reflect a shift from traditional reactive project management to proactive, data-driven decision-making aimed at improving accuracy, efficiency, and overall project outcomes.

Despite these advancements, AI adoption in the construction industry remains uneven and fragmented. A typical construction project progresses through seven distinct phases of the project lifecycle: *Project Conception and Initiation*, *Planning and Design*, *Preconstruction*, *Procurement*, *Construction*,

*Closeout, and Post-construction* (Park, 2009; Penn State University, 2020). Each of these phases involves different stakeholders, decisions, and data needs. However, research literature suggests that most current AI applications are concentrated on specific tasks or phases, such as safety during construction or document analysis during procurement. Other important stages, such as project conception, closeout, and long-term facility operations, are still underexplored (Datta et al., 2024; Egwim et al., 2023). This limits the potential of AI to deliver integrated value across the project delivery.

There is a lack of a unified framework for benchmarking AI applications to foster a structured, holistic understanding of how AI can be utilized across a project's lifecycle. Correspondingly, companies, especially those new to AI, are facing significant challenges in developing informed, responsive AI adoption and implementation strategies, which will limit AI's potential to deliver integrated value across project delivery. A lifecycle-based approach can provide valuable insights and clarity, helping to identify gaps and guide more effective AI adoption and deployment.

To address this gap, this research study conducts a systematic review of AI applications based on peer-reviewed literature published between 2010 and 2024, and a structured metadata analysis. By organizing and comparing the literature by project lifecycle phases, AI techniques, key business processes supported, AI tools and platforms, and impact evaluation methods, the study provides insights into where AI generates the greatest impact and where gaps remain. The goal is to support more strategic planning for AI integration across lifecycle phases and lay the groundwork for more consistent, data-informed project delivery. This study is guided by the following two research questions (RQs):

- **RQ1:** In what ways is AI being used across construction project life cycles?
- **RQ2:** What are the impacts of AI, and in what ways are these impacts being assessed?

### Related Works

Several literature reviews have investigated AI applications in the construction industry, each contributing distinct insights while also demonstrating clear limitations. Datta et al. (2024) conducted a PRISMA-based review of 70 studies and found that AI is increasingly being adopted in planning and execution; however, the procurement, closeout, and post-construction phases received minimal attention. Egwim et al. (2023) reviewed AI applications across the construction value chain but did not organize their findings by lifecycle stages, which limits the ability to track how AI use evolves from project conception to operation. Regona et al. (2024) focused on sustainable and smart infrastructure, whereas Pan and Zhang (2021) emphasized the use of computer vision in defect detection. Jin et al. (2019) and Wang et al. (2020) examined cost estimation, scheduling, and NLP-based contract analysis, respectively. These reviews are informative but tend to center on either specific technologies or isolated project phases, leaving the broader lifecycle context underdeveloped.

To provide clarity, **Table 1** summarizes key focus areas, methods, and limitations of these reviews. However, several additional studies, not included in the table due to narrower thematic scopes, offer further insights. Adewale et al. (2024) emphasized the importance of sustainability-focused AI, particularly for operational performance monitoring. Abioye et al. (2021) discussed AI for managing cost, schedule, and safety risks but framed findings by functional task rather than lifecycle stage. Rabbi and Jeelani (2024) analyzed AI for construction safety across text, vision, and audio modalities. Technique-focused surveys, such as Xu et al. (2020) on computer vision and Wu et al. (2022) on NLP, further enrich domain-specific understanding. Yet, across these reviews, applications in procurement, handover, and facility operations remain significantly less explored than planning and construction.

**Table 1.** Summary of exemplary systematic reviews on AI applications in construction

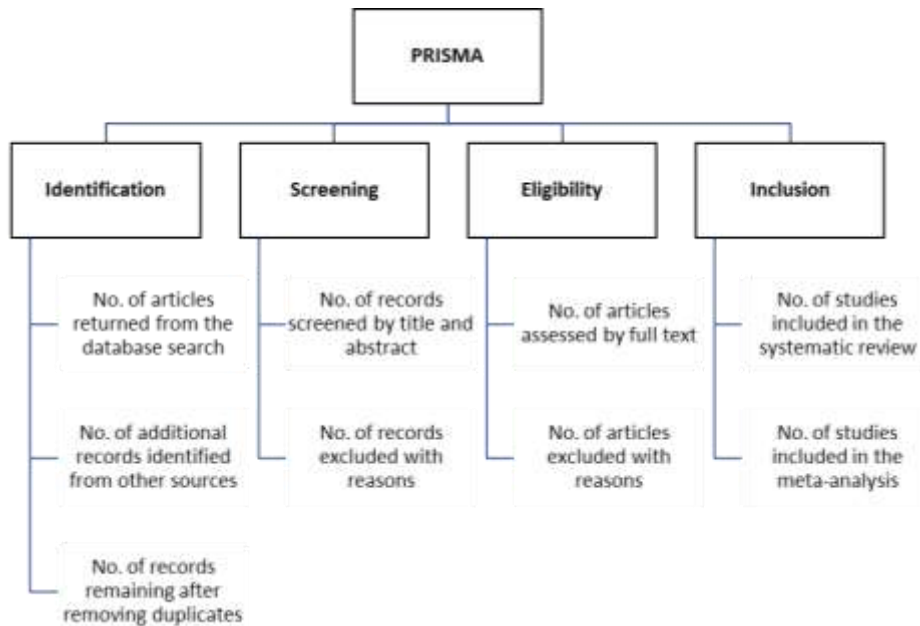
Authors	Database	Search Keywords	# of Articles Reviewed	Timespan	Focus
Datta et al. (2024)	Scopus, Web of Science, Google Scholar	Artificial intelligence, machine learning, construction	70 out of 1,180	2012–2023	AI and ML in construction, focused on planning and execution stages
Egwim et al. (2023)	IEEE Xplore, Scopus, ASCE Library	AI in construction value chain, automation, digital construction	52 out of 900	2010–2022	Mapping AI implementation across construction value chain, emphasis on design and operations
Regona et al. (2024)	Web of Science, Google Scholar	AI, sustainable construction, smart infrastructure	45 out of 680	2013–2023	Sustainability goals, AI contributions to smart and green construction practices
Pan and Zhang (2021)	Scopus, Web of Science, ScienceDirect	Computer vision, defect detection, and construction	38 out of 550	2005–2021	Computer vision techniques for construction monitoring, defect detection
Wang et al. (2020)	ASCE Library, Engineering Village, Web of Science	Natural language processing, AI, contracts, construction documents	20 out of 300	2015–2020	NLP applications in contract review and construction document management
Jin et al. (2019)	Scopus, ScienceDirect, ASCE Library	AI, cost estimation, scheduling, machine learning	34 out of 610	2008–2018	AI for cost prediction, risk analysis, and schedule optimization
Zhou et al. (2021)	Engineering Village, IEEE Xplore	Generative design, AI, architectural design	28 out of 420	2010–2021	AI-based design automation, particularly in early design stages

Methodologically, reviews such as those by Egwim et al. (2024), Datta et al. (2024), and Adewale et al. (2024) followed systematic review protocols aligned with the PRISMA guidelines, ensuring transparency and reproducibility. Rabbi and Jeelani (2024) also employed structured search procedures, whereas Chen et al. (2024) combined bibliometric mapping with systematic review and synthesis. In contrast, narrative reviews, such as those by Abioye et al. (2021), provided thematic depth but lacked replicability. Although some studies claimed to make meta-analytical contributions, true meta-analysis was rarely feasible due to heterogeneous research designs and evaluation metrics.

This study addresses these gaps through a PRISMA-based review, combined with metadata-driven classification and an interactive Power BI dashboard that enables dynamic exploration of AI applications across lifecycle stages, techniques, and functional domains. This approach supports a comprehensive and actionable understanding of AI adoption patterns across the project lifecycle.

### Methodology

The review followed a structured process based on the PRISMA methodology (Moher et al., 2009), proceeding in three main stages: literature identification, article screening and selection, and metadata-driven analysis (**Figure 1**). The search targeted peer-reviewed journal articles published between 2010 and 2024, reflecting the period during which AI gained significant traction in research (Egwim et al., 2024; Datta et al., 2024). Major databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar, were selected for their comprehensive coverage of engineering, computing, and construction management literature (Adewale et al., 2024; Chen et al., 2024).



**Figure 1.** The PRISMA process for literature review.

An initial set of 1,245 articles was retrieved using keyword combinations referencing AI technologies and construction contexts, such as “AI in construction,” “machine learning in construction,” “computer vision for site monitoring,” and “NLP for safety analysis.” Keyword sets were grouped to capture both textual and visual data modalities, following the structured search logic outlined in reviews such as those by Rabbi and Jeelani (2024). An additional 45 records were identified through backward reference tracing, resulting in a total of 1,290 articles. Removal of duplicates reduced this to 1,050 unique records.

Screening was conducted according to PRISMA-aligned inclusion and exclusion criteria. Articles were included if they: (1) presented a real or simulated application of AI in construction, (2) addressed at least one construction lifecycle phase, and (3) were published in peer-reviewed outlets. Studies were excluded if they focused on theoretical AI discussions without implementation, addressed non-construction domains such as general real estate analytics, or fell outside the 2010–2024 range. After

title and abstract screening, 230 articles were assessed in full text, and 60 were retained for final analysis. Each article was then coded using a structured metadata framework adapted from Haddaway et al. (2022), capturing attributes such as AI technique (e.g., machine learning, deep learning, NLP, symbolic reasoning), tool or platform used, construction lifecycle phase addressed, business function (e.g., scheduling, safety, cost control), and evaluation method (real-world dataset, simulation, or case study). This approach aligns with structured synthesis practices in recent reviews (Datta et al., 2024; Rabbi and Jeelani, 2024).

## Results and Findings

Following the PRISMA methodology, 60 peer-reviewed articles published between 2010 and 2024 were selected from an initial pool of 1,290. This ensures the findings are based on high-quality, relevant studies, which contribute to understanding: 1) *how artificial intelligence is currently being used across construction project lifecycles (RQ1)* and identifying: 2) *the impacts these applications have generated, as well as how those impacts are being evaluated (RQ2)*. The study organizes all findings across seven distinct phases of the project lifecycle. A comprehensive metadata schema was used to extract and structure key attributes from each study, including *AI techniques, functional roles, tools used, business processes supported, and impact evaluation methods*.

### *Key Finding 1: Uneven AI Adoption Across the Project Lifecycle*

The distribution of AI applications is heavily skewed toward the mid-project stages, where operational risks and data availability are highest (Table 2). This concentration reveals both the current strengths of AI adoption and significant gaps in its application. The high concentration in the Construction and Planning phases is driven by the availability of structured data from schedules, BIM models, and site monitoring, making them ideal for ML-based optimization and DL-based pattern recognition. However, the underrepresentation in Procurement, Closeout, and Post-construction signals a major missed opportunity. These phases involve significant contractual complexities, high costs, and long-term asset performance implications that could benefit immensely from AI-enabled solutions.

**Table 2.** Distribution of AI Studies Across Lifecycle Phases

Lifecycle Phase	Number of Studies	Percentage of Total
Construction	25	41%
Planning and Design	22	36%
Procurement	9	15%
Project Conception	8	13%
Preconstruction	6	10%
Closeout	6	10%
Post-construction	5	8%

### *Key Finding 2: Dominance of Machine Learning and Task-Oriented Applications*

The analysis of *AI techniques* and their *functional roles* reveals a clear preference for established methods applied to specific, well-defined problems. Machine Learning stands out as the most prevalent technique due to its effectiveness with the structured datasets commonly found in construction for tasks such as scheduling, cost control, and sensor analysis. The growing presence of Deep Learning and Computer Vision reflects a shift toward handling unstructured data, particularly for visual tasks like defect detection and progress tracking (**Table 3**).

**Table 3.** AI Techniques Employed

AI Technique	Number of Studies	Percentage of Total
Machine Learning (ML)	48	79%
Deep Learning (DL)	20	33%
Natural Language Processing (NLP)	9	15%
Computer Vision (CV)	8	13%
Expert Systems / Rule-Based AI	6	10%
Large Language Models (LLMs)	4	7%

The functional roles of AI applications are task-oriented, predominantly used for optimization, risk assessment, and predictive modeling, reflecting an industry focus on addressing core challenges in resource management, safety, and forecasting:

- Optimization (22 studies): Improving resource allocation, schedule performance, and cost efficiency.
- Risk Assessment (19 studies): Evaluating safety hazards, cost overruns, and schedule uncertainties.
- Predictive Modeling (17 studies): Forecasting outcomes such as project delays and equipment failures.
- Automation (13 studies): Assisting or replacing repetitive manual tasks like progress tracking.
- Pattern Recognition (8 studies): Detecting anomalies, trends, and inefficiencies in data.

In terms of specific AI tools and platforms adopted, while most research relies on custom-built models, the use of standardized platforms is growing, indicating a move toward more scalable and replicable AI solutions, as summarized in Table 4.

**Table 4.** Common AI tools and platforms

Tool / Platform	Primary AI Technique	Application Area
Keras on TensorFlow	Deep Learning	Material categorization, business intelligence
H2O Framework in R	Machine Learning	Risk prediction, safety assessment
TensorFlow - BIM	Computer Vision	Modular object detection, quality inspection
Azure ML Platform	Machine Learning	Semantic tagging of BIM objects
ChatGPT	Natural Language Processing	Automated scheduling support, resource planning

*Key Finding 3: AI Support for Core Business Processes*

Mapping AI applications to specific business processes provides a clear view of where technology is delivering strategic value. *Risk management, scheduling, and resource management* are the most supported domains, while significant gaps remain in other critical areas (Table 5).

**Table 5.** Common AI support for key business processes

Business Process	Number of Studies	Common AI Applications
Risk Management	24	Hazard prediction, probabilistic modeling
Scheduling	14	Delay analysis, resource planning
Resource Management	14	Workforce and equipment allocation
Quality Control	13	Defect detection, visual inspections

Safety Assessment	13	Worker monitoring, site safety
Cost Estimation	10	Budget prediction, cost modeling
Procurement Management	10	Vendor ranking, bid analysis
Contract Management	5	Document compliance, change tracking
Design Optimization	5	Parametric modeling, energy efficiency
Operations and Maintenance	3	Predictive maintenance, asset monitoring

In summary, the findings related to RQ1 indicate that a critical barrier to maximizing AI's value is its highly fragmented application (Table 6). Many AI solutions are designed to solve problems within a single project phase, with minimal integration across the entire lifecycle.

**Table 6.** Pervasive fragmentation and lack of integration

Integration Level	# of Studies	% of Total	Typical Phase Overlaps
Single Phase Only	45	74%	One specific phase (e.g., Construction only)
Two-Phase Integration	10	16%	Planning and Construction, Procurement and Construction
Three or More Phases	5	8%	Planning, Construction, and Post-construction
Full Lifecycle Integration	1	2%	All phases from conception to post-construction

This fragmentation prevents the development of continuous decision-support systems that can leverage data from early planning stages to inform long-term operations and maintenance. The single study that achieved full lifecycle integration used a digital twin framework, suggesting a potential pathway to more comprehensive AI applications.

*Key Finding 4: Gaps in Impact Assessment and Evaluation*

Turning to RQ2, the review examined whether AI impacts were reported and which evaluation methods were used to assess them. According to **Table 7**, the methods used to evaluate AI effectiveness reveal a significant disconnect between technical performance and tangible project-level impact. Most studies evaluated AI models based on their technical performance, using metrics such as prediction accuracy, classification reliability, and computational efficiency. While these metrics confirm whether an AI model functions properly, they do not fully capture its practical contribution to project delivery outcomes. A smaller subset of studies reported more tangible performance improvements, including reduced inspection time, lower rework rates, improved worker safety awareness, and decreased schedule delays. However, these impacts were often confined to isolated case studies and lacked standardized evaluation frameworks that would allow performance comparisons across different project contexts. This reliance on technical metrics limits industry leaders' ability to build a strong business case for AI investment based on proven, real-world returns.

**Table 7.** AI model validation and evaluation methods

Validation and Evaluation Method	Number of Studies	Percentage of Total
Accuracy/Precision Metrics (e.g., R <sup>2</sup> , RMSE)	30	49%
Time/Cost Improvement Measurements	16	26%
Simulation-Based Validation	11	18%
Impact Modeling / Scenario Analysis	6	10%
No Clear Evaluation Method	4	7%

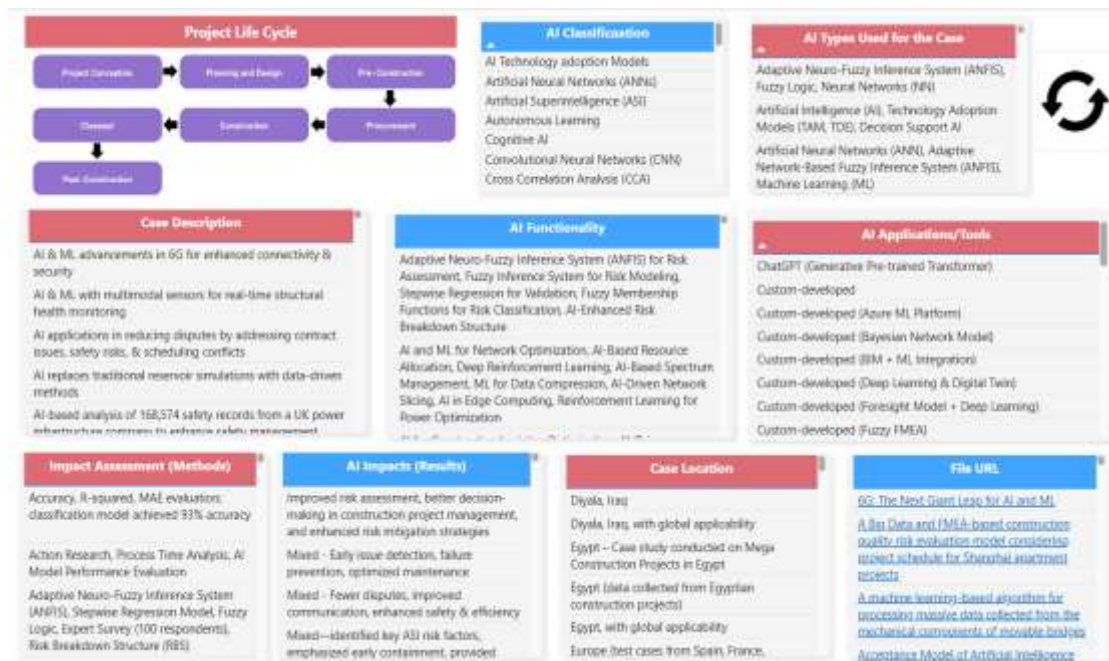
In this study, a clear distinction is made between *technical model validation* and *true impact evaluation*. Technical model validation refers to performance-based metrics such as accuracy, RMSE, and precision that assess the predictive reliability of AI models. In contrast, true impact evaluation requires pre- and post-implementation comparisons at the project or process level to measure tangible outcomes, such as time savings, cost reductions, risk mitigation, or safety improvements.

*The Power BI Dashboard: A Dynamic Tool for Insight*

To ensure that the findings of this study can be explored interactively rather than interpreted only through static summaries, all metadata extracted from the reviewed studies were incorporated into an interactive Power BI dashboard (**Figure 2**). The dashboard allows users – from project managers to academic researchers – to:

- Filter and Visualize Data: Interactively explore AI applications by lifecycle phase, AI type, functional role, geographical location, and evaluation method.
- Identify Gaps and Opportunities: Quickly identify underrepresented lifecycle phases (e.g., Closeout) or functional roles (e.g., automation) to guide future research and investment.
- Support Decision-Making: Enable practitioners to find relevant AI tools and case studies for specific project needs, such as a preconstruction manager seeking risk assessment tools.

By bridging the gap between academic research and industry application, the dashboard serves as a living resource for promoting connected, intelligent, and data-driven construction practices.



**Figure 2.** User interface of the proposed Power BI dashboard

### Conclusion and Future Directions

This research study provides a clear, lifecycle-based perspective on the state of AI in the construction industry. It reveals an accelerating but uneven adoption landscape, where immense potential is often constrained by a fragmented, phase-specific approach and a lack of focus on holistic, project-level impact. The AI lifecycle mapping attempted in this study provides a crucial structure for overcoming these limitations. The primary findings can be distilled into three critical takeaways:

1. **Fragmented Application:** AI is heavily concentrated in planning and construction, leaving significant value untapped in crucial phases like procurement and closeout. The vast majority of solutions are siloed within a single project phase.
2. **A Gap in Measurement:** The evaluation of AI success is dominated by technical performance metrics, with a significant lack of focus on quantifiable business outcomes like cost savings, risk reduction, and return on investment (ROI).
3. **Emerging Potential:** While Machine Learning is the current workhorse, the rapid emergence of Generative AI for automating knowledge work signals a disruptive shift. Companies that master these tools first will gain a significant advantage in pre-construction, contract management, and client communication.

Future research should prioritize the development of integrated AI systems that span multiple phases of the project lifecycle. There is a pressing need for studies that incorporate real-time data, expand geographic coverage to underrepresented regions, and focus on long-term value creation, including qualitative impacts such as organizational change and stakeholder satisfaction. By adopting a lifecycle-oriented perspective, the industry can move beyond isolated solutions toward a future of truly connected and intelligent project delivery.

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