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Predictive Analytics and AI in Construction Project Management: Redefining Risk Mitigation and Strategic Decision Making

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ABSTRACT

Construction projects are persistently affected by schedule delays, cost overruns and complex, interdependent risks. This narrative review examines how predictive analytics and artificial intelligence (AI) are being applied in construction project management, with particular attention to risk mitigation and strategic decision making. Drawing on peer-reviewed reviews and empirical studies, the paper synthesises evidence across four application areas: schedule and delay prediction, cost forecasting, quality and safety prediction, and risk assessment. The literature shows that supervised machine learning models, including neural network ensembles, support vector machines, tree-based ensembles and, increasingly, deep learning, can predict delay risk, cost and schedule success, and several safety outcomes from project and site data with useful accuracy. Integration with Building Information Modelling (BIM), Internet of Things (IoT) sensing and digital twins is expanding the data available for prediction. However, reported performance comes largely from single-dataset studies, and robust evidence on organisation-level benefits and return on investment remains limited. Persistent barriers include fragmented and low-quality data, poor interoperability, limited model interpretability, skills shortages, high deployment costs and cultural resistance to change. The paper offers recommendations for construction organisations, technology vendors, educational institutions and policymakers, and identifies research priorities, including multi-project validation, interpretable models and rigorous evaluation of economic impact.

Keywords: *Predictive analytics; artificial intelligence; construction project management; risk mitigation; strategic decision making; machine learning; data-driven management; narrative review*

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1. INTRODUCTION

Construction project management has long been characterised by uncertainty, complexity and poor cost and schedule performance. In an analysis of 258 transport infrastructure projects, costs were underestimated in almost nine out of ten projects, and actual costs were on average 28% higher than estimated (Flyvbjerg et al., 2002). Delay is similarly pervasive: in a survey of large building projects in Saudi Arabia, 70% of projects experienced time overrun, and change orders were the most frequently cited cause (Assaf & Al-Hejji, 2006). The industry's traditional reactive approach, which relies heavily on experience-based decision making and historical precedent, has struggled to manage this complexity. Predictive analytics and artificial intelligence (AI) offer a route toward proactive, data -driven project management that could change how construction professionals approach risk mitigation and strategic decision making (Pan & Zhang, 2021).

Predictive analytics in construction project management involves applying statistical techniques, machine learning algorithms and data mining methods to historical and real-time project data in order to forecast outcomes, identify emerging risks and support decisions (Bilal et al., 2016). This approach enables project managers to move beyond reactive problem-solving toward predictive and prescriptive strategies that address issues before they escalate.

The adoption of AI in construction has been driven by the proliferation of digital project management tools, the growing volume of data generated through Building Information Modelling (BIM), and advances in computational capability (Darko et al., 2020; Sacks et al., 2020). These developments have created opportunities to apply predictive analytics to scheduling, cost control, quality assurance and risk management.

Research activity has grown rapidly: one review counted 15 publications on machine learning in construction in 2017 and 153 in 2022 (Datta et al., 2024). Industry adoption, however, remains at an early stage (Darko et al., 2020; Regona et al., 2022), and successful deployment depends on data quality, model selection, organisational readiness and change management (Abioye et al., 2021).

The objective of this narrative review is to examine how predictive analytics and AI are reshaping risk mitigation and strategic decision making in construction project management. It synthesises current applications, appraises the strength of the evidence on their effectiveness, identifies implementation challenges, and offers strategic recommendations for organisations seeking to use predictive technologies to improve project outcomes.

2. METHODOLOGY

This study is a narrative review of the literature on predictive analytics and AI in construction project management. A narrative rather than systematic design was adopted because studies in this field are heterogeneous in their methods, datasets and outcome measures, which limits formal quantitative pooling.

2.1 Literature Search

Literature was identified through searches of Scopus, Web of Science, IEEE Xplore, the ASCE Library and Elsevier ScienceDirect, using combinations of the keywords "predictive analytics," "artificial intelligence," "construction project management," "risk mitigation," "machine learning," and "decision support systems." Boolean operators were used to refine searches, and the reference lists of relevant reviews were screened to identify additional sources. Priority was given to peer-reviewed reviews and empirical studies published from 2016 onward, supplemented by earlier foundational studies on construction cost and schedule performance.

2.2 Inclusion Criteria

Sources were included if they (1) described the application of predictive analytics or AI in construction project management, (2) reported empirical performance data or synthesised such evidence, (3) addressed risk mitigation or decision making, and (4) provided sufficient methodological detail for appraisal.

2.3 Synthesis Approach

Evidence was synthesised thematically into application areas (schedule, cost, quality and safety, and risk), decision-support domains and implementation barriers. Where individual studies reported quantitative performance, results are described together with the data and context from which they were obtained; they are not pooled, because study designs and performance metrics differ. No primary data were collected for this review.

3. FINDINGS

3.1 Current State of Predictive Analytics in Construction Project Management

The literature describes a rapidly evolving set of predictive applications spanning the project lifecycle, with the greatest concentration in the planning and construction stages (Datta et al., 2024). Neural networks, genetic algorithms, fuzzy logic and machine learning have been the most widely used AI methods in architecture, engineering and construction research (Darko et al., 2020). Current applications can be grouped into four areas: schedule prediction, cost forecasting, quality and

safety prediction, and risk assessment.

3.1.1 Schedule Prediction and Delay Risk

Schedule prediction models use historical project data, planning information, resource availability and progress data to forecast outcomes and flag potential delays. Wang et al. (2012) trained artificial neural network ensembles and support vector machines on early-planning (Project Definition Rating Index) scores from 92 building projects in Taiwan and obtained satisfactory predictions of cost and schedule success. Gondia et al. (2020) applied decision-tree and naive Bayes classifiers to construction delay risk prediction, and Egwim et al. (2021) compared ten machine learning algorithms using expert survey data on delay factors, finding that a stacked ensemble outperformed the individual models. Table 1 summarises the main model families reported in this literature.

Table 1. Predictive model families reported for schedule, cost and delay prediction in construction

Model family	Typical inputs	Reported strengths and limitations	Example studies
Artificial neural network ensembles	Early-planning scores; project characteristics	Capture non-linear relationships; require sizeable training data; limited interpretability	Wang et al. (2012)
Support vector machines	Early-planning scores; project characteristics	Effective on small, high-dimensional datasets; sensitive to parameter tuning	Wang et al. (2012)
Decision trees and naive Bayes	Delay-risk factors and project attributes	Relatively interpretable; simpler models may underfit complex interactions	Gondia et al. (2020); Egwim et al. (2021)
Tree-based and stacked ensembles	Delay-factor ratings; injury-report attributes	Strong predictive skill in reported studies; performance depends on hyperparameter optimisation	Egwim et al. (2021); Tixier et al. (2016)
Deep learning (e.g., CNNs)	Images, video and sensor streams	Suited to unstructured data; "black box" behaviour and high computational cost	Akinosho et al. (2020)

Qualitative synthesis compiled by the authors from the cited studies; it does not report pooled accuracy values.

3.1.2 Cost Forecasting and Control

Predictive cost models analyse historical cost data, project characteristics and progress information to forecast final costs and identify likely overruns, and cost estimation is among the most frequently cited AI opportunities in construction (Abioye et al., 2021). Given evidence that cost estimates for major projects are systematically optimistic (Flyvbjerg et al., 2002), models that learn from completed-project data can provide an independent check on estimates, although they cannot by themselves correct for deliberate misrepresentation in the estimating process.

3.1.3 Quality and Safety Prediction

Deep learning, particularly convolutional neural networks, has been applied to structural health monitoring, defect detection, site safety and equipment activity recognition (Akinosho et al., 2020). In safety, Tixier et al. (2016) applied random forest and stochastic gradient tree boosting models to 4,398 construction injury reports and achieved skilful prediction of injury type, energy type and body part affected, but found no predictive skill for injury severity.

3.2 Risk Mitigation Through Predictive Analytics

Predictive analytics extends construction risk management from largely qualitative, judgement-based assessment toward quantitative, data-driven estimation of risk likelihood and consequences (Pan & Zhang, 2021).

3.2.1 Risk Identification and Prediction

Empirical studies show that supervised models can classify delay risk and safety outcomes with useful predictive skill (Egwim et al., 2021; Gondia et al., 2020; Tixier et al., 2016). However, most models are trained and tested on a single dataset, and like-for-like comparisons with conventional risk assessment methods on the same projects are rare. The size of the improvement over traditional practice has therefore not yet been reliably established. Table 2 maps the main risk categories to the AI approaches reported for them.

Table 2. Construction risk categories and AI approaches reported in the literature

Risk category	AI or analytics approach reported	Representative sources
Schedule delay	Supervised classifiers and ensembles trained on delay factors and project attributes	Gondia et al. (2020); Egwim et al. (2021)
Cost overrun	Neural network ensembles and SVMs predicting cost success from early-planning data	Wang et al. (2012); Flyvbjerg et al. (2002)

Risk category	AI or analytics approach reported	Representative sources
Safety incidents	Random forest and gradient tree boosting on injury-report attributes	Tixier et al. (2016)
Quality and defects	Computer vision and deep learning for defect detection and structural health monitoring	Akinosho et al. (2020); Darko et al. (2020)
Data and integration	Big data platforms; BIM–IoT integration; digital twins	Bilal et al. (2016); Tang et al. (2019); Opoku et al. (2021)

Qualitative synthesis compiled by the authors from the cited studies.

3.2.2 Proactive Risk Response

Early warnings allow project teams to act before risks materialise, for example by re-sequencing work, reallocating resources or adjusting procurement. Reviews identify the planning stage, where accurate forecasting has the greatest leverage, as the phase in which AI offers the most potential (Regona et al., 2022).

3.2.3 Risk Quantification and Impact Assessment

Predictive models can provide probabilistic estimates of risk likelihood and impact, and AI-based optimisation and process-mining techniques can support the evaluation of alternative responses (Pan & Zhang, 2021). The value of these estimates depends on the quality and representativeness of the underlying project data.

3.3 Strategic Decision Making

Predictive analytics can support complex decisions across multiple project dimensions by supplying data-driven forecasts to complement professional judgement.

3.3.1 Resource Optimisation Decisions

AI-based optimisation methods can analyse resource availability, productivity patterns and project requirements to recommend allocation strategies (Pan & Zhang, 2021), and big data analytics can reduce time spent on repetitive planning tasks (Regona et al., 2022). Table 3 contrasts traditional and AI-enhanced approaches across key decision areas.

Table 3. Traditional and AI-enhanced approaches across strategic decision areas

Decision area	Traditional approach	AI-enhanced approach
Resource allocation	Experience-based planning	Data-driven optimisation of resource assignment
Procurement timing	Fixed schedules	Demand forecasting from progress and market data
Quality control	Reactive inspection	Predictive quality assurance and automated defect detection
Change management	Manual impact assessment	Automated analysis of schedule and cost impacts
Vendor selection	Historical reputation	Predictive modelling of supplier performance
Schedule compression	Rule-based acceleration	Optimisation-based scenario evaluation

Conceptual comparison compiled by the authors; performance gains in each area remain to be quantified in controlled studies.

3.3.2 Investment and Technology Decisions

Predictive models can inform decisions on technology investment, equipment purchase and process improvement. Reviews advise construction firms to prioritise AI investments in areas with clear business cases and measurable returns on research and development expenditure (Regona et al., 2022).

3.3.3 Portfolio Management and Project Selection

Using predictive analytics to assess the risk–return profiles of candidate projects and to balance project portfolios is conceptually attractive, but it has received little empirical attention in the construction literature and is identified here as an area for future research.

3.4 Technology Implementation Patterns

3.4.1 Implementation Stages

The literature favours phased adoption, beginning with pilot applications in areas with a clear business case before scaling up, because the fragmented structure of the industry makes data acquisition and retention difficult (Regona et al., 2022).

3.4.2 Technology Architecture and Integration

Predictive analytics depends on integrating data from BIM models, project management software, IoT sensors and external databases (Bilal et al., 2016; Tang et al., 2019). Sacks et al. (2020) identify the semantic enrichment of BIM models and the development of data representations suited to machine learning as prerequisites for realising AI's potential. Digital twins offer a further integration route, although their implementation in construction

remains limited and mostly confined to single lifecycle phases (Opoku et al., 2021).

4. DISCUSSION

4.1 Impact on Project Management Practice

The literature points to a shift from reactive to proactive project management, in which predictive insights help managers anticipate issues and optimise decisions before problems affect outcomes (Pan & Zhang, 2021). This shift has implications for roles: project managers increasingly need data literacy and analytical skills alongside coordination skills, and the shortage of professionals with both construction and AI expertise is a recurring concern (Abioye et al., 2021; Akinosho et al., 2020).

4.2 Risk Management Paradigm Shift

Predictive risk models offer quantitative, repeatable assessments to complement traditional qualitative methods. Their limits must also be recognised. Some outcomes, such as injury severity, could not be predicted from observable precursors (Tixier et al., 2016), and opaque "black box" models are difficult for practitioners to trust and audit (Akinosho et al., 2020). For high-stakes decisions, inherently interpretable models may be preferable to post-hoc explanations of complex models (Rudin, 2019).

4.3 Economic Impact and Return on Investment

Claims of large returns on investment appear frequently in industry commentary, but peer-reviewed evidence quantifying the organisation-level economic impact of predictive analytics in construction is scarce. High initial deployment costs are a recognised barrier (Abioye et al., 2021), and firms are advised to prioritise investments with clear business cases and measurable returns (Regona et al., 2022). Rigorous cost–benefit evaluations across multiple projects and organisations are therefore a research priority.

4.4 Implementation Challenges and Barriers

Several challenges continue to limit adoption. Predictive models require large volumes of high-quality historical data, which many construction organisations lack, and data preprocessing has been identified as the most challenging and time-consuming step in construction knowledge discovery (Bilal et al., 2016).

4.4.1 Data Integration Challenges

Construction data are fragmented across lifecycle stages and stored in heterogeneous formats, which complicates interoperability and integration (Bilal et al., 2016; Tang et al., 2019). Integrating BIM with IoT devices and making BIM data usable by machine learning algorithms remain active research problems (Sacks et al., 2020; Tang et al., 2019).

4.4.2 Organisational Resistance and Change Management

Cultural resistance to new technology, high deployment costs and concerns about security and governance hinder adoption (Abioye et al., 2021), and the fragmented structure of the industry adds further barriers (Regona et al., 2022). Successful implementation therefore requires deliberate change management alongside technical investment.

4.4.3 Skills Gap and Training Requirements

Effective use of predictive analytics requires competencies that are often lacking in traditional construction organisations, including data science skills and the ability to interpret model outputs; addressing this gap requires sustained investment in training (Abioye et al., 2021; Akinosho et al., 2020).

4.5 Future Trends and Emerging Technologies

Advanced AI techniques, including deep learning and natural language processing, together with smart robotics, AI-enabled IoT and digital twins, are expected to broaden predictive capabilities (Akinosho et al., 2020; Pan & Zhang, 2021). Richer real-time data from IoT sensors and site monitoring (Tang et al., 2019) and digital-twin platforms (Opoku et al., 2021) may enable continuous, site-level prediction, although these applications are still at an early stage.

5. CONCLUSIONS

This review indicates that predictive analytics and AI have considerable potential to change how construction projects manage risk and make strategic decisions, but that the evidence base is still developing.

5.1 Key Findings

Predictive performance: Empirical studies show that machine learning models can predict delay risk, cost and schedule success, and several safety outcomes with useful accuracy. Most evidence, however, comes from single-dataset studies, and the effect of these tools on project outcomes at scale has not been established.

Risk management: Predictive analytics supports a shift from qualitative, reactive risk management toward quantitative, proactive approaches, subject to limits of data quality, predictability and interpretability.

Strategic decisions: Predictive tools can inform resource allocation, procurement, change management and investment decisions, but controlled evaluations of their decision-making benefits are scarce.

Maturity and adoption: Research output is growing rapidly, whereas industry adoption remains at an early stage and is constrained by data, integration, cost, skills and cultural barriers.

5.2 Industry Implications

Organisations that build sound data foundations and adopt predictive analytics in a phased, evidence -led way are likely to be better placed to manage risk and improve project performance. As data infrastructure and skills mature, predictive analytics is likely to become an increasingly important part of construction project management.

5.3 Limitations and Future Research

This study is a narrative rather than systematic review, so the selection of sources may be subject to bias, and the heterogeneity of study designs and metrics precluded meta-analysis. No primary data were collected. The literature is concentrated on large projects and organisations, and on single datasets.

Future research should validate models across multiple projects and organisations, compare predictive tools with conventional methods on the same projects, develop interpretable models suitable for high-stakes decisions, rigorously evaluate economic returns, and examine how predictive analytics can be adapted for smaller construction firms with different resource constraints.

6. RECOMMENDATIONS

Based on the findings of this review, the following recommendations are proposed for different stakeholder groups.

6.1 For Construction Organisations

Develop a data strategy: Organisations should prioritise comprehensive data strategies that ensure data quality, accessibility and integration across project management systems, supported by data governance frameworks and standardised data collection.

Adopt in phases: Implementation should begin with pilot projects in controlled settings and clear business cases before expanding to enterprise-wide deployment, allowing capabilities to develop while limiting risk.

Invest in talent: Organisations should invest in training that builds both technical data-analysis skills and the ability of decision makers to interpret and question model outputs.

Establish centres of excellence: Dedicated centres of excellence can build specialised capability, share good practice and accelerate adoption across projects and business units.

6.2 For Technology Vendors

Industry-specific solutions: Vendors should develop construction-specific tools that address industry requirements and integrate with existing construction management systems.

Usability and transparency: Solutions should prioritise ease of use and transparent, interpretable outputs to support adoption by professionals with limited technical backgrounds.

Implementation support: Vendors should provide data integration services, training and ongoing technical support to ensure successful deployment.

6.3 For Educational Institutions

Curriculum integration: Construction management and engineering programmes should integrate predictive analytics and data science education.

Research collaboration: Academic institutions should collaborate with industry on applied research that addresses practical implementation challenges and evaluates outcomes rigorously.

Professional development: Universities should offer continuing education to help practising construction professionals build predictive analytics capability.

6.4 For Industry Associations and Policymakers

Standards development: Industry associations should develop standards and good-practice guidance for implementing and validating predictive analytics.

Knowledge sharing: Professional associations should create forums for sharing experience and data to accelerate industry-wide learning.

Policy support: Policymakers should consider incentives for technology adoption and investment in workforce development to support the construction industry's digital transformation.

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