International Journal of Latest Research in Engineering and Technology (IJLRET)
ISSN: 2454-5031
www.ijlret.com || Volume 12 - Issue 08 || August 2026 || PP. 01-20
DOI: 10.56581/IJLRET.12.07.01-20

Artificial Intelligence-Enabled Digital Project Management in Construction: A Critical Review of Applications, Project Performance Outcomes and Adoption Barriers

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Abstract: The construction sector accounts for roughly 13% of global gross domestic product and employs about 7% of the world's workforce, yet it remains among the least digitised industries and continues to record chronic cost and schedule failure. Artificial intelligence (AI) is widely promoted as the corrective, and the volume of scholarship has grown steeply from fewer than ten journal articles annually before 2018 to 125 in 2025 within the cost, time and safety domains alone. What this has not resolved is the relationship between reported model accuracy and realised project performance. This paper critically reviews the peer-reviewed evidence on AI-enabled digital project management (DPM) in construction, asking where AI is being applied across project management knowledge areas, what performance outcomes are actually demonstrated, and what impedes organisational adoption. Thestudyfirstly reported predictive accuracy being high and, in cost estimation, approaching saturation, with coefficients of determination above 0.99 now routinely claimed. Second, that accuracy rests on fragile foundations validation are overwhelmingly retrospective, samples are small and geographically bounded, and where hold-out testing is disclosed, the degradation is severe, one delay-prediction study reporting 47.2% testing accuracy against 74.5% on training. Third, adoption barriers cluster in the organisational domain, and the research literature systematically under-attends them: bibliometric analysis of 4,668 publications found socio-technical barriers occupying 4.6% of the literature against 46% practitioner salience, a ratio of 4.7 practitioners per publication. Study argues that these are one phenomenon rather than three. Predictive accuracy on retrospective single-context data has become a poor proxy for managerial value, and the field's dominant metric now obscures more than it reveals. An integrated framework is proposed in which technical capability is mediated by deployment maturity and organisational absorptive capacity, and in which feedback latency operates as an under-theorised determinant of diffusion.

Keywords: artificial intelligence; digital project management; project performance; machine learning; technology adoption

1. Introduction

Few industries carry as much economic weight while performing as poorly against their own delivery targets. Construction contributes approximately 13% of global gross domestic product and provides employment for around 7% of the world's workers (Gao et al., 2026; McKinsey Global Institute, 2017). Global construction output stood at some US$13 trillion in 2023 and is projected to reach US$22 trillion by 2040 (McKinsey & Company, 2024). Against that scale, the sector's productivity record is unflattering, labour productivity growth has averaged around 1% annually over two decades compared with 2.8% for the world economy as a whole, and closing the gap with the wider economy would add an estimated US$1.6 trillion in annual value (McKinsey Global Institute, 2017).

The delivery statistics are equally uncomfortable. Average cost overrun in global construction has been put at 28%, rising to 47% in the United Kingdom, while only 35% of South African construction projects are completed within their estimated cost (Sepasgozar et al., 2022). Examining 65 projects across ten sectors, Ansar et al. (2016) reported an average delay rate of 42.7%. Safety performance compounds the picture, in the United States, fatalities from falls, slips and trips rose 5.9% and account for close to 20% of all workplace deaths, with construction responsible for 46.2% of these fatal incidents (Gao et al., 2026).

These are not new problems, and they have not proved responsive to conventional management remedies. That persistence is itself diagnostic, since it suggests the binding constraint is informational and analytical rather than procedural. Construction decisions are made under conditions of high uncertainty, fragmented data ownership and severe time pressure, which is precisely the decision environment in which computational augmentation should offer most leverage.

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Digital project management (DPM) describes the reconfiguration of planning, monitoring and control functions around integrated digital data flows rather than document exchange. Its infrastructure in construction has accreted over two decades, encompassing building information modelling (BIM), common data environments, cloud-based collaboration platforms, Internet of Things (IoT) sensing and, more recently, digital twins (Jiang et al., 2021; Karmakar and Delhi, 2021; Sepasgozar, 2021). Artificial intelligence (AI) does not sit alongside this stack so much as inside it. Machine learning consumes the data these systems generate and returns predictions, classifications and optimisations that would otherwise depend on expert judgement (Pan and Zhang, 2021). The distinction matters for how the phenomenon should be evaluated, treating AI as a discrete technology invites assessment on technical criteria such as accuracy and computational efficiency, whereas treating it as an enabling layer within DPM invites assessment on managerial criteria whether a forecast changed a decision, and whether that decision improved the outcome.

Scholarly attention has followed the promise closely. Publication volume on AI in construction cost, time and safety management rose from fewer than ten journal articles annually before 2018 to 125 in 2025, including an 86% single-year increase between 2021 and 2022 (Gao et al., 2026). Reviewing AI-enabled project management across sectors, Taboada et al. (2023) found machine learning to be the dominant technique, with its most encouraging contributions lying in the planning, measurement and uncertainty performance domains through improved forecasting and decision support.

Eurostat data for 2024 place AI uptake among European construction enterprises at 7.2%, among the lowest of any sector measured and far below information and communications technology (OECD, 2025). The Royal Institution of Chartered Surveyors, surveying more than 2,200 professionals globally, found that while some experimentation is widespread, only 1.5% reported use across multiple processes and fewer than 1% reported fully embedded, organisation-wide deployment (RICS, 2025). A decade of accelerating research output has coincided with almost no measurable diffusion into organisational practice.

That gap is where this review locates itself and capable syntheses already exist. Abioye et al. (2021) mapped AI applications, opportunities and challenges across construction. Darko et al. (cited in Gao et al., 2026) conducted a scientometric analysis identifying machine learning, neural networks, genetic algorithms and fuzzy systems as dominant methods, while Akinosho et al. (2020) concentrated on deep learning in structural health monitoring and safety. Gao et al. (2026) reviewed 392 Scopus-indexed articles on AI in construction cost, time and safety management. What these share is a tendency to catalogue rather than interrogate. Applications are mapped and techniques classified, but the evidentiary quality of reported performance is rarely examined whether validation was prospective or retrospective, whether hold-out testing was conducted, whether sample sizes support the generalisability claimed. A second and related separation runs through the field: technical reviews and adoption reviews proceed on parallel tracks, so that studies applying the TechnologyOrganisationEnvironment (TOE) framework or the Unified Theory of Acceptance and Use of Technology (UTAUT) to construction AI rarely engage with the performance literature, and vice versa. The discipline can consequently describe both high reported accuracy and negligible diffusion without accounting for the relationship between them.

What these reviews share is a tendency to catalogue rather than interrogate. Applications are mapped and techniques classified, but the evidentiary quality of reported performance is rarely examined, whether validation was prospective or retrospective, whether hold-out testing was conducted, whether sample sizes support the generalisability claimed. Gao et al. (2026) observe that a considerable proportion of studies remain at proof-of-concept stage, though the observation is not developed into a structured appraisal. A second and related separation runs through the field: technical reviews and adoption reviews proceed on parallel tracks, so that studies applying the TechnologyOrganisationEnvironment (TOE) framework or the Unified Theory of Acceptance and Use of Technology (UTAUT) to construction AI rarely engage with the performance literature, and vice versa. The discipline can consequently describe both high reported accuracy and low observed diffusion without accounting for the relationship between them. Evidence from developing economies compounds the difficulty, being thinly represented in synthesis work despite adoption dynamics differing materially, with infrastructure deficits, skills gaps and regulatory ambiguity operating as first-order constraints rather than secondary frictions (Osuizugbo and Alabi, 2022; Ibrahim et al., 2026).

This paper accordingly synthesises and critically appraises the peer-reviewed evidence on AI-enabled digital project management in construction, connecting demonstrated technical performance to project outcomes and organisational adoption. Three questions organise the review: in which project management knowledge areas AI is applied and through which techniques; what performance outcomes are reported and how methodologically robust the supporting evidence is; and what technological, organisational and environmental factors constrain adoption at firm level. Running beneath these is an integrative concern with how the relationship between technical performance and organisational uptake should be theorised.

Methodologically, the review appraises validation rigour rather than accepting reported metrics at face value, annotating each performance claim with the basis on which it was established. Empirically, it brings the performance and adoption literatures into a single analytical frame and stratifies barrier evidence by economic context rather than aggregating across it. Theoretically, it advances an integrated framework in which technical capability is mediated by deployment maturity and organisational absorptive capacity, and argues that predictive accuracy, the field's dominant metric has become a poor proxy for managerial value.

2. Theoretical Background

For the purposes of this study, AI-enabled DPM is defined as the application of computational learning, reasoning or perception techniques to the planning, monitoring, control and decision functions of construction project delivery, operating on digitally captured project data. Three boundary conditions apply. The system must perform a task conventionally requiring human judgement; it must operate on project data rather than purely physical or material data; and its output must inform a project management decision rather than a design or engineering computation alone.

This excludes structural analysis software, parametric design tools and rule-based clash detection, none of which involve learning. It includes cost forecasting models, schedule risk classifiers, computer vision safety monitoring, natural language processing of contract and incident documentation, and generative scheduling assistants.

The field's technological trajectory falls into three eras that remain useful for situating individual studies: rule-based expert systems through the 1980s and 1990s, which codified human expertise but transferred poorly between projects; statistical machine learning from the late 1990s to around 2012, enabling data-driven cost forecasting, risk analysis and resource optimisation; and deep learning from 2012 onward, leveraging convolutional architectures and GPU capacity to support real-time progress monitoring and hazard detection (Sobieraj and Metelski, 2026).

2.1 AI techniques in construction project management

Table 1 sets out the principal technique families and their characteristic applications, synthesised from the reviewed corpus.The pattern worth noting is that hybridisation has become the norm rather than the exception. Pure single-algorithm studies now largely serve as baselines against which coupled architectures are benchmarked, a maturation signal, but also a source of methodological inflation.

Table 1: AI technique families in construction project management

Technique family	**Representative methods**	**Principal CPM applications**	**Indicative sources**
Supervised regression	ANN, SVM/SVR, RF, XGBoost, LightGBM, KNN, ridge/LASSO	Cost estimation, cost overrun prediction, duration forecasting	Coffie and Cudjoe (2024); Chen *et al.* (2025); Gao *et al.* (2026)
Supervised classification	Decision trees, Naïve Bayes, logistic regression, AutoML	Delay risk classification, accident severity prediction	Gondia*et al.* (2020); Zhu *et al.*(2021)
Deep learning	CNN, LSTM, DNN, deep MLP, transformers	Progress monitoring, unsafe behavior recognition, cost index forecasting	Ding *et al.*(2018); Yang *et al.*(2023); Cao and Ashuri (2020)
Computer vision	YOLO variants, Faster R-CNN, YOLACT, instance segmentation	PPE detection, guardrail detection, worker and equipment tracking	Nath *et al.* (2020); Hayat and Morgado-Dias (2022); Kolar *et al.* (2018)
Natural language processing	Text mining, topic modelling, transformer LMs, RAG	Incident narrative classification, contract risk extraction, schedule generation	Tixier *et al.*(2016); Goh and Ubeynarayana (2017); Prieto *et al.* (2023); Saka *et al.*, cited in Emerald (2026)
Metaheuristic optimization	GA, PSO, ACO, Tabu Search, Pelican Optimization	Timecost trade-off, resource levelling, hyperparameter tuning	Yaseen *et al.* (2020); Kulejewski and Rosłon, (2023)
Probabilistic reasoning	Bayesian networks, dynamic Bayesian networks, fuzzy inference	Risk assessment, fall-risk state estimation	Piao *et al.*(2021)
Hybrid	ANN-metaheuristic,	Integrated costduration	Kedir *et al.*(2022)

Technique family	Representative methods	Principal CPM applications	Indicative sources
architectures	DNN-SVR, RLagent-based models	prediction, adaptive scheduling	

2.2 Theoretical framing of adoption

Three theoretical lenses recur in the construction AI adoption literature, and each captures a different level of analysis.

The TechnologyOrganisationEnvironment (TOE) framework, developed by Tornatzky and Fleischer (1990), locates innovation adoption in the interaction of three firm-level contexts: technological (characteristics of the innovation and existing technology base), organisational (size, structure, slack resources, managerial support) and environmental (competitive pressure, regulation, partner readiness). Oliveira and Martins (2011) and Baker (2011) established its applicability to inter-organisational contexts, and it has since become the dominant lens for construction technology adoption research. Its advantage for this review is that it operates at firm level, which is where AI investment decisions are actually made.

Diffusion of Innovations (DOI) theory contributes the attributes governing adoption rate, relative advantage, compatibility, complexity, trialability and observability. It is frequently integrated with TOE to combine structural and perceptual explanation (Sánchez et al., 2025; Ogundipe et al., 2027).

The Technology Acceptance Model (TAM) and its extension UTAUT/UTAUT2 operate at individual level, explaining behavioural intention through performance expectancy, effort expectancy, social influence and facilitating conditions. Recent construction studies have combined UTAUT2 with TOE to bridge individual and organisational determinants, finding behavioural intention ($\beta = 0.313$, $p < 0.01$), facilitating conditions ($\beta = 0.279$, $p < 0.01$) and compatibility with existing design practice ($\beta = 0.155$, $p < 0.01$) all significant predictors of AI adoption among design engineers (Katebi& Tehrani, 2025).

Socio-technical systems theory supplies a fourth and increasingly salient lens, holding that technology implementation requires alignment between technical and social subsystems, and that adoption failures typically arise from misalignment between the two rather than from technical deficiency (Sobieraj and Metelski, 2026). This framing is important to the argument developed in this study, because it predicts precisely the pattern the empirical adoption literature reports.

This review adopts TOE as its primary organising structure for the analysis of adoption barriers, drawing on DOI, UTAUT and socio-technical theory where their mechanisms are salient. The rationale is pragmatic: the barriers reported in the empirical literature are predominantly structural, and TOE accommodates structural explanation without forcing it through a perceptual filter.

3. Methodology

This paper is a critical review in the sense defined by Grant and Booth (2009), whose typology distinguishes fourteen review forms by their approach to search, appraisal, synthesis and analysis. A critical review does not seek exhaustive coverage. It seeks instead to demonstrate extensive engagement with a literature, to evaluate that literature's quality rather than merely summarise its content, and to arrive through analysis at a conceptual contribution typically a model, hypothesis or reframing that the constituent studies do not themselves supply (Oladimeji et al., 2025; Ogundipe et al., 2025). Search is purposive rather than systematic; appraisal is central rather than procedural; synthesis is narrative and conceptual; and the output is judged on the strength of its argument rather than the completeness of its sample (Ogundipe et al., 2026).

That form was selected deliberately, and the reasoning should be stated plainly since it bears on how the findings ought to be read. The questions driving this review are evaluative rather than aggregative. Asking whether reported model accuracy constitutes credible evidence of managerial value is not a question that a more exhaustive sample would answer better; it is a question about the epistemic status of a body of claims, and it requires close reading of how those claims were established. Furthermore, metric heterogeneity across the performance literature studies report R^2, RMSE, MAE, MAPE, accuracy, precision, recall, F1, kappa and mAP in inconsistent combinations, frequently without confidence intervals or baseline comparisons precludes meta-analysis regardless of sample size. Where quantitative pooling is not feasible, the marginal value of exhaustive retrieval falls sharply while the value of critical appraisal rises.

Snyder (2019) makes the complementary point that the choice of review methodology should follow from the research purpose rather than from convention, and that reviews aiming to critique and synthesise legitimately draw on research articles, books and other published texts through a search strategy that is purposive rather than systematic. Torraco (2005) and Kunisch et al. (2023) similarly position conceptually

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oriented reviews as a distinct and legitimate mode of scholarly inquiry rather than as a weaker approximation of systematic review

3.1 Literature identification

Literature was identified through Scopus and Web of Science, supplemented by targeted forward and backward citation tracking from key sources and by purposive searching for evidence on under-represented contexts, particularly developing economies. Table 2 sets out the scope.

Table 2: Scope and literature base of the review

Element	**Specification**
Review type	Critical review (Grant and Booth, 2009)
Primary sources	Scopus; Web of Science
Supplementary	Backward and forward citation tracking; purposive searching for developing-economy and practitioner evidence
Concept blocks	AI and machine learning techniques; project management functions; construction and built environment
Principal window	2015–2026, reflecting the emergence of Industry 4.0 and the subsequent inflection in construction AI publication
Earlier sources	Retained where they constitute the foundation of a framework in current use (e.g. Tornatzky and Fleischer, 1990; Torraco, 2005; Grant and Booth, 2009)
Publication types	Peer-reviewed journal articles; authoritative practitioner and institutional surveys where they supply evidence unavailable in the academic literature (RICS, 2025; OECD, 2025)
Language	English
Selection principle	Purposive, prioritising studies reporting performance metrics, adoption determinants or implementation evidence, and those with sufficient methodological transparency to permit appraisal

The inclusion of institutional survey evidence warrants comment. The academic literature contains almost no large-scale measurement of actual organisational adoption, a gap the RICS (2025) survey of more than 2,200 professionals and the OECD (2025) analysis of Eurostat enterprise data fill directly. Excluding such sources on formal grounds would have meant excluding the best available evidence on the review's third question. They are treated as what they are cross-sectional, self-reported and not peer-reviewed and triangulated against academic findings wherever possible.

3.2 Appraisal and synthesis

Sources were appraised against five criteria: clarity of aim, appropriateness of method, transparency of data provenance and scale, adequacy of validation, and explicitness of limitations. Two of these carried particular weight given the review's concerns. The first is whether a study reported hold-out or cross-validated performance rather than training performance alone; the second is whether dataset provenance and size were disclosed. These proved unusually discriminating, and where studies failed them their reported metrics are presented in this review with that failure noted rather than silently accepted.

Synthesis proceeded along two tracks. Performance evidence was tabulated by knowledge area to permit cross-study comparison, annotated throughout with validation approach — this annotation is the analytical move that distinguishes the present review from prior catalogues. Adoption evidence was organised deductively into TOE categories, with sub-themes derived inductively within each, and stratified by economic context.

3.3 Bibliometric profile of the field

Although a critical review does not generate its own corpus statistics, the shape of the field can be characterised from published bibliometric evidence. Gao et al. (2026), screening 5,873 Scopus records to a final dataset of 392 articles on AI in construction cost, time and safety management, report the annual distribution shown in Table 3 and Figure 1.

Table 3: Annual publication volume, AI in construction cost, time and safety management (Gao et al., 2026)

Year	2013 - 2017	2018	2020	2021	2022	2023	2024	2025
Journal Articles	< 10 per year	12	23	22	41	56	78	125

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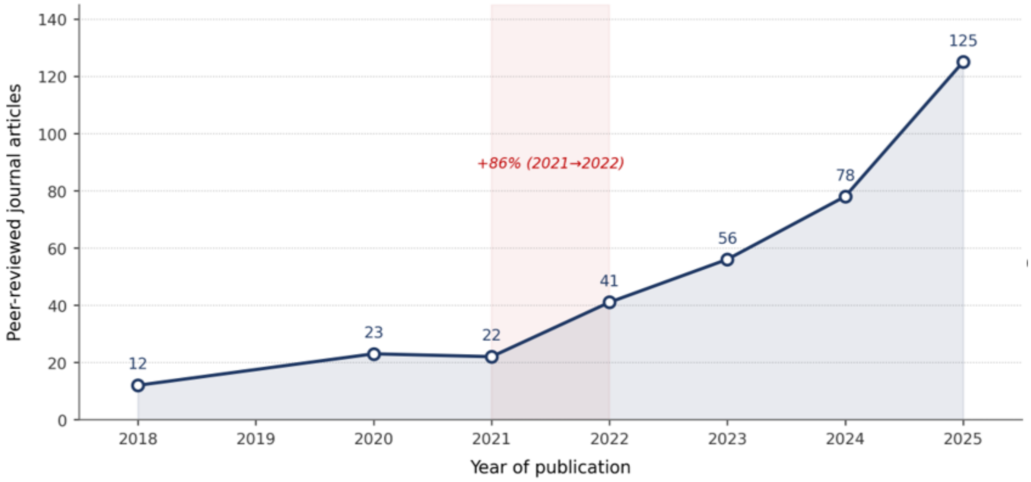

Figure 1. Growth in AIinconstructionprojectmanagement publications, 2018 - 2025 (Gao et al., 2026).

The inflection reported between 2021 and 2022 of an 86% year-on-year increase precedes the public release of general-purpose generative models, so it cannot be attributed to that event. It more plausibly reflects the maturation of data infrastructure and the post-pandemic acceleration of construction digitalisation. The second is the near doubling into 2025, which does coincide with generative AI diffusion and is likely to include a substantial volume of exploratory work whose durability is untested. Readers should treat 2024 to 2025 output with more caution than volume alone would suggest.

4. Key Insights and Discussion

4.1 Applications of AI across project management knowledge areas

4.1.1 Cost management

Cost management is the most heavily populated application domain, and within it cost estimation attracts the largest share of studies (Gao et al., 2026). Four sub-applications are distinguishable: cost estimation, cost overrun prediction, cost index forecasting, cost control and cost optimisation.

I. **Estimation**: Early work established that neural architectures outperform regression on nonlinear cost relationships. Rafiei and Adeli (2018) combined a deep Boltzmann machine with a back-propagation neural network, trained on 372 low- to mid-rise buildings in Tehran and augmented with economic variables and indices, achieving mean squared error between 0.021 and 0.125 across architectures and training ratios, and outperforming both BPNN-only and SVM-only baselines. Ensemble methods subsequently displaced single networks in many settings: Alshboul et al. (2022) found extreme gradient boosting outperforming deep neural networks and random forest in green building cost estimation with prediction accuracy of 0.96.

II. **Overrun prediction**: This is where the sharpest performance claims appear. Coffie and Cudjoe (2024) applied XGBoost to Ghanaian projects completed between 2016 and 2018, reporting RMSE 0.202, MSE 0.041, MAE 0.069 and MAPE 0.306, and used SHAP values to rank feature importance, initial contract amount, number of floors, scope changes and initial duration emerged as the dominant predictors. Arabiat et al. (cited in Gao et al., 2026) compared ANN and KNN, with ANN achieving $R^2 = 0.9913$ and RMSE $= 0.021$ against KNN's $R^2 = 0.9233$ and RMSE $= 0.1304$. Al Mnaseer et al. (2023) integrated Tabu Search with ANN across 191 Jordanian projects, reporting 92.19% accuracy and $R^2 = 0.9385$ for both cost and time overrun prediction.

III. **Index forecasting:**Wang and Ashuri (2017) applied KNN and PERT to Engineering News-Record construction cost index forecasting, achieving MAPE of 0.19% for short-term, 0.28% for mid-term and 0.78% for long-term horizonssubstantially outperforming conventional time-series approaches. Cao and Ashuri (cited in Gao et al., 2026) demonstrated LSTM architectures handling highly volatile road construction cost data.

IV. **Control and optimisation**:Mohammed et al. (2022) applied ANN, multiple linear regression and SVM to earned value management indicators, and the results are instructive precisely because they are mixed: MLR achieved higher raw accuracy (95.89% SPI, 96.89% CPI, 95.91% TCPI) than ANN (83.09%, 90.83%, 82.88%) or SVM (94.12%, 71.76%, 84.82%), though ANN and SVM recorded lower MAPE. That a linear model can outperform learning methods on a well-specified control problem is a finding the field tends to under-report.

4.1.2 Time and schedule management

Genetic algorithms dominated early schedule automation work, as Faghihi et al. (2015) found reviewing the period 1985–2014. The methodological centre of gravity has since shifted toward learning-based and hybrid approaches. Kedir et al. (2022) integrated reinforcement learning with agent-based modelling, improving project duration by 15% in two case studies and matching GA and PSO performance in a third. Yan et al. (2023) coupled computer vision with earned duration management for prefabricated building progress monitoring, achieving MAPE of 9.3%.

Delay risk prediction has proved harder than cost prediction, and the difference is diagnostic. Gondia et al. (2020) built decision tree and Naïve Bayes classifiers on Egyptian building projects; the decision tree achieved 74.5% training accuracy but only 47.2% on testing, while Naïve Bayes achieved 78.4% and 51.2% respectively. Yaseen et al. (2020) reported 91.67% accuracy from a random forest–genetic algorithm hybrid on Iraqi projects, and Egwim et al. (2021) demonstrated ensemble-of-ensembles approaches. Shirazi and Toosi (cited in Gao et al., 2026) reported a deep multilayer perceptron achieving 94.36% accuracy, 93.81% F1, 95.85% precision, 94.07% recall and a kappa of 91.36% on Iranian dam projects.

The dispersion here is the testing accuracy ranging from 47% to 94% across broadly similar problem formulations is not primarily a difference in algorithmic capability. It reflects differences in dataset construction, class balance and, critically, whether hold-out testing was performed at all. This will be further discussed.

4.1.3 Safety management

Safety is the most operationally mature domain. Seven application areas are identifiable: worker safety monitoring, on-site safety monitoring, PPE detection, safety report text analysis, fall risk monitoring, accident prediction, and hazard identification and risk assessment (Gao et al., 2026).

PPE detection has become something of a benchmark task. Nath et al. (2020) developed three YOLO-based approaches on the crowd-sourced Pictor-v3 dataset, trading accuracy against speed: 63.1% mAP at 13 FPS, 72.3% mAP at 11 FPS, and 85.6% mAP at lower frame rates. Hayat and Morgado-Dias (2022) reported YOLOv5x achieving 92.44% mAP, 92.00% accuracy, 89.24% recall and 90.81% F1, with performance sustained under low light. Kang et al. (2022) integrated weather-variation parameters into a YOLACT instance segmentation model, achieving mAP50:95 of 0.755 ± 0.009 at 19.2 ± 0.04 FPS across light, dark, rain, snow and fog conditions, a rare and welcome instance of explicit environmental robustness testing.

Behaviour recognition has advanced similarly. Ding et al. (2018) combined CNN and LSTM to detect hazardous worker behaviours, achieving 97% accuracy in distinguishing safe from unsafe actions. Yang et al. (2023) proposed a transformer-based STR-Transformer reaching 88.7% average precision on eight-frame inputs. Kolar et al. (2018) applied transfer learning to guardrail detection, reporting 96.5% accuracy and F1.

Text analysis of safety documentation forms a distinct strand. Tixier et al. (2016) classified incident narratives using random forest, achieving F1 of 0.95; Goh and Ubeynarayana (2017) reported substantially wider variance using SVM, with F1 between 0.45 and 0.92 across categories. Zhu et al. (2021) compared eight algorithms for accident severity prediction, with AutoML achieving the highest F1 at 84.4%.

4.1.4 Risk management and decision support

Probabilistic approaches retain a distinctive role here because risk management requires calibrated uncertainty rather than point prediction. Piao et al. (2021) integrated computer vision with a dynamic Bayesian network to classify fall risk second-by-second from worker posture, PPE status and equipment proximity, issuing medium-risk alerts above a 52.3% probability threshold. Bayesian networks have also been applied to delay risk in tunnel boring machine projects and to schedule risk inference through Bayesian Monte Carlo simulation.

Natural language processing has opened contract and tender documentation to systematic risk extraction, with text-mining applications analysing contractor risk in invitations to bid and in engineering, procurement and construction contracts (Choi et al., 2021).

4.1.5 Integration with BIM and digital twins

AI rarely operates on raw project data in mature deployments; it operates on structured models. Pan and Zhang (2021) proposed a BIM–data mining integrated digital twin framework for advanced project management, and this integration pattern has since become dominant. Baghdadi(2025) proposed a five-level maturity ladder that remains the most useful organising device in this literature: Level 1, BIM for visualisation; Level 2, BIM-supported simulation; Level 3, BIM with IoT for monitoring; Level 4, BIM with AI for prediction; Level 5, full digital twins with automated control.

The distinction between a digital twin and an advanced BIM model is the bidirectional, near-real-time data connection between physical asset and digital model (Sepasgozar, 2021; Jiang et al., 2021). Most construction implementations remain at Levels 3 and 4. Publication volume in digital twin research rose approximately 80% between 2019 and 2024, with Asia and particularly China leading contributions (Qiu et al., 2025).

This is also the domain where research attention is most heavily concentrated, and Section 4.3.5 argues that the concentration is itself a problem.

4.1.6 Generative AI and large language models

This is the newest and least settled strand. Large language models are being deployed in three integration patterns: standalone task-specific assistants; embedded modules connected to BIM, digital twin or IoT systems via APIs and knowledge graphs; and retrieval-augmented generation pipelines combining information retrieval with generative reasoning (Gao et al., 2026).

Documented applications include automated architectural detailing the NADIA system integrating GPT with Revit achieved 83.3% accuracy in exterior wall detailing while reducing manual effort (Gao et al., 2026), automated safety inspection, building energy modelling and design change management. In scheduling, Prieto et al. (2023) used a GPT model to generate and optimise construction schedules from user input, producing coherent task breakdowns with duration deviations within one day and worker-count deviations within two.

The limitations are as consistently reported as the capabilities. NADIA's dependence on predefined JSON rules and rigid prompt chains constrains adaptability to novel design intents (Gao et al., 2026). Multimodal frameworks degrade sharply in data-scarce contexts. Ghimire et al. (2024) identify hallucination, data confidentiality and validation difficulty as recurring adoption obstacles for text-based generative models in construction, and Sobieraj and Metelski (2026) note that generative hallucination compounds the sector's pre-existing data-quality vulnerability rather than operating independently of it.

4.1.7 Synthesis of the application map

The Table 4 consolidates the application map.

Table 4: AI applications mapped to project management knowledge areas

PM knowledge area	Dominant applications	Dominant techniques	Maturity
Cost	Estimation, overrun prediction, index forecasting, control, optimisation	ANN, SVM, RF, XGBoost, LSTM, hybrid metaheuristics	Validated retrospectively; limited live deployment
Time	Planning/scheduling, delay risk prediction, time optimisation, cycle time	GA, RF, ANN, RL-ABM, deep MLP, NLP/LLM	Project-specific case validation
Safety	PPE detection, behaviour monitoring, fall risk, text analysis, accident prediction	CNN, YOLO variants, transformers, RF, SVM, Bayesian networks	Closest to operational deployment
Risk	Risk classification, contract risk extraction, probabilistic risk inference	Bayesian networks, NLP, ensemble classifiers	Emerging
Integration	BIM-AI, digital twin analytics	Data mining on BIM, IoT fusion, knowledge graphs	Predominantly Levels 3-4 of five
Communication / documentation	Schedule generation, document reasoning, reporting	LLMs, RAG pipelines	Experimental

4.2 Project performance outcomes and evidentiary quality

4.2.1 Reported performance

Table 5 consolidates comparable performance evidence. It is deliberately annotated with dataset scale and validation approach, because these fields carry more interpretive weight than the headline metrics.

4.2.2 The validation gap

Reading Table 5 vertically rather than horizontally produces the central finding of this review.

Where hold-out testing is explicitly reported, performance falls sharply. Gondia et al. (2020) is the clearest case: a decision tree achieving 74.5% on training data drops to 47.2% on testing below the rate a naive

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majority-class classifier would achieve on a balanced binary problem. Naïve Bayes performs comparably poorly. The authors report this transparently, which is precisely why the study is valuable; the concern is that most studies in the corpus do not report the comparison at all, leaving readers unable to distinguish genuine generalisation from memorisation.

At the other extreme, Abed et al. (2022) report ridge regression achieving R^2 of 1.0 with MAPE and RMSE of exactly 0.00 on road construction cost estimation. A perfect fit on real-world cost data is not a strong result; it is a diagnostic signal of leakage, over-fitting or evaluation performed on training data. That such a result passes into a published systematic review without flagging illustrates a broader appraisal weakness in this literature.

Table 5: Comparative performance of AI models in construction project management

Study (as reported)	**Domain**	**Technique**	**Dataset / context**	**Reported performance**	**Validation basis**
Rafiei and Adeli (2018)	Cost estimation	DBM + BPNN	372 buildings, Tehran	MSE 0.021–0.125	Retrospective, train/verify split
Alshboul*et al.* (2022)	Green building cost	XGBoost vs DNN, RF	Green building projects	Prediction accuracy 0.96	Retrospective
Coffie and Cudjoe (2024)	Cost overrun	XGBoost + SHAP	Ghanaian projects, 2016–2018	RMSE 0.202; MAE 0.069; MAPE 0.306	Retrospective archival
Arabiat et al. (2023)	Cost overrun	ANN vs KNN	Jordan	ANN R^2 0.9913, RMSE 0.021; KNN R^2 0.9233	Retrospective
Al Mnaseer et al. (2023)	Cost & time overrun	ANN + Tabu Search	191 projects, Jordan	92.19% accuracy; R^2 0.9385	Retrospective
Abed et al. (2022)	Road cost estimation	Ridge regression, RF, KNN, LASSO	Road projects	Ridge: R^2 1.0; MAPE 0.00; RMSE 0.00	**Reported without hold-out; implausible**
Wang and Ashuri (2017)	Cost index	KNN, PERT	ENR CCI series	MAPE 0.19% (short), 0.28% (mid), 0.78% (long)	Time-series backtest
Mohammed et al. (2022)	Cost control (EVM)	ANN, MLR, SVM	EVM indicators	MLR 95.89–96.89%; ANN 82.88–90.83%	Retrospective
Gondia*et al.* (2020)	Delay risk	Decision tree; Naïve Bayes	Egypt, buildings	DT 74.5% train / **47.2% test**; NB 78.4% / **51.2%**	**Hold-out reported**
Yaseen *et al.* (2020)	Delay risk	RF + GA	Iraq	91.67% accuracy	Survey-derived, cross-validated
Shirazi and Toosi (2023)	Delay risk	Deep MLP-NN	Iranian dam projects	94.36% accuracy; F1 93.81%; κ 91.36%	Retrospective
Kedir et al. (2022)	Duration optimisation	RL + agent-based model	3 case studies	15% duration improvement (2 cases)	Simulation-based
Yan et al. (2023)	Progress monitoring	CV + earned duration	Prefabricated buildings	MAPE 9.3%	Single-project case
Nath *et al.* (2020)	PPE detection	YOLO (3 approaches)	Pictor-v3, ~1,500 images	63.1% / 72.3% / 85.6% mAP	Held-out test set
Hayat and Morgado-Dias (2022)	Helmet detection	YOLOv5x	Construction sites	mAP 92.44%; F1 90.81%	Held-out test set
Kang et al. (2022)	Site monitoring	YOLACT + weather augmentation	5 weather conditions	mAP50:95 0.755 ± 0.009; 19.2 FPS	**Robustness-tested**
Ding et al. (2018)	Unsafe behaviour	CNN + LSTM	Video data	97% binary; 92% four-class	Controlled conditions
Tixier et al. (2016)	Incident	Random forest	Incident	F1 0.95	Cross-validated

International Journal of Latest Research in Engineering and Technology (IJLRET)
ISSN: 2454-5031
www.ijlret.com || Volume 12 - Issue 08 || August 2026 || PP. 01-20
DOI: 10.56581/IJLRET.12.07.01-20

Study (as reported)	Domain	Technique	Dataset / context	Reported performance	Validation basis
	classification		narratives		
Goh and Ubeynarayana (2017)	Accident narratives	SVM	Narrative corpus	F1 0.45–0.92 (by class)	Cross-validated
Zhu et al. (2021)	Accident severity	AutoML (of 8 algorithms)	Accident records	F1 84.4%	Cross-validated

Three structural problems compound this:

i. **Sample scale:** Datasets are small by machine learning standards. Rafiei and Adeli's (2018) 372 buildings and Al Mnaseer et al.'s (2023) 191 projects are among the larger cost datasets in the corpus. Nath et al.'s (2020) Pictor-v3 comprises approximately 1,500 annotated images modest against general computer vision benchmarks. With samples of this order, reported R^2 values above 0.99 warrant scepticism rather than celebration.

ii. **Geographic and typological boundedness:** Models are trained on projects from single countries and often single project types, Tehran residential buildings, Ghanaian public works, Iranian dams, Jordanian projects. Procurement regimes, cost structures, labour markets and regulatory environments differ so materially between these contexts that transfer cannot be assumed. Gao et al. (2026) acknowledge this, noting that performance is typically demonstrated under limited conditions with insufficient evidence of cross-context applicability.

iii. **Metric heterogeneity:** Studies report R^2, RMSE, MAE, MAPE, accuracy, precision, recall, F1, kappa and mAP in inconsistent combinations, frequently without confidence intervals or significance testing against baselines. Quantitative pooling is consequently not feasible on this literature, which is itself a finding worth stating plainly.

4.2.3 From model accuracy to project performance

The more consequential gap is conceptual. Almost all reported outcomes are model-level: how closely a prediction matched a recorded value. Very few are project-level: whether the prediction changed a decision, and whether that decision improved cost, schedule or safety performance relative to a counterfactual.

The exceptions are instructive. Kedir et al. (2022) report a 15% duration improvement, a project-level outcome, though derived from simulation rather than live delivery. Kulejewski and Rosłon (2023) report net present value improving from 27,822 to 27,915 and a sustainability value index from 0.9761 to 0.9910 under an ANN-augmented scheduling procedure; the gains are real but modest, and the contrast between a 0.15% NPV improvement and the headline accuracy figures elsewhere in the literature is worth sitting with. Gao et al. (2026) identify only one clear instance of live deployment in their 392-article corpus, an AI-based safety early warning system at the Jinji Lake Tunnel using field monitoring data for continuous risk assessment.

At industry level, the McKinsey Global Institute's estimate that digital transformation yields productivity gains of 14–15% and cost reductions of 4–6% (McKinsey & Company, 2019) remains the most cited quantification of realised benefit but it addresses digitalisation broadly, is consultancy-derived rather than peer-reviewed, and predates current AI capability. The field lacks a credible peer-reviewed estimate of AI's project-level effect.

4.2.4 Domain asymmetry in deployment readiness

Gao et al. (2026) observe that safety applications sit closer to deployment than cost or time applications, and attribute this to the availability of continuous visual and sensor data, the immediacy of safety risk, and the feasibility of validating safety systems in live environments. The reasoning holds and is worth extending.

Safety monitoring produces continuous ground truth, a worker either wears a helmet or does not, verifiable within seconds. Cost and schedule prediction produce ground truth only at project completion, potentially years later, by which point the model, the market and the organisation have all changed. This is a structural feedback asymmetry, not a temporary state of the art, and it implies that cost and time applications will remain harder to validate and slower to mature regardless of algorithmic progress. Any research agenda that ignores this will keep producing accuracy improvements that cannot be operationally confirmed.

4.3 Adoption barriers

Despite the performance evidence, diffusion remains minimal. Eurostat data for 2024 place AI adoption among European construction enterprises at 7.2%, below accommodation and food services (7.8%) and

International Journal of Latest Research in Engineering and Technology (IJLRET)
ISSN: 2454-5031
www.ijlret.com || Volume 12 - Issue 08 || August 2026 || PP. 01-20
DOI: 10.56581/IJLRET.12.07.01-20

transportation and storage (9.2%), and far below the information and communications technology sector (OECD, 2025). The RICS (2025) survey of over 2,200 professionals found organisation-wide embedded use below 1%, with a further 7% of respondents unsure whether their organisation used AI at all, an uncertainty the report reasonably reads as evidence of capabilities embedded in tools without clear labelling or of absent implementation strategy. Table 6 organises the barrier evidence using TOE.

Table 6: Adoption barriers by TOE dimension

TOE dimension	**Barrier**	**Evidence base**
Technological	Data availability, quality and fragmentation	RICS (2025); Sobieraj and Metelski (2026); Gao *et al.* (2026)
	Limited model generalisability across project contexts	Gao *et al.* (2026)
	Interoperability with legacy systems and BIM environments	RICS (2025); Gao*et al.* (2026)
	Opacity of model reasoning; limited explainability	Coffie and Cudjoe (2024); Chen *et al.* (2025)
	Infrastructure and connectivity constraints	Ibrahim*et al.* (2026); Osuizugbo and Alabi (2022)
Organisational	Skills and AI proficiency gaps	RICS (2025); Osuizugbo*et al.* (2026); Adebowale and Agumba (2024)
	High implementation cost (hardware, licensing, expertise)	Gao *et al.* (2026); Sánchez *et al.* (2025)
	Cultural resistance and fear of job displacement	Osuizugbo and Alabi (2022); Sobieraj and Metelski (2026)
	Absence of digital strategy and executive sponsorship	RICS (2025); Bhattacharya and Momaya (2021)
	Firm fragmentation and project-based discontinuity	McKinsey Global Institute (2017)
Environmental	Legal and liability uncertainty	Rosenbaum & Bartels (2026)
	Weak or absent regulatory frameworks	Osuizugbo and Alabi (2022)
	Data privacy, worker consent and surveillance concerns	Gao *et al.* (2026)
	Client and supply-chain readiness asymmetry	Katebi& Tehrani (2025)
	Competitive pressure (enabler as well as barrier)	Katebi& Tehrani (2025); Na *et al.* (2024)

4.3.1 Technological barriers

Gao et al. (2026) identify limited historical records, small sample sizes and difficulties in data collection and validation as compromising model accuracy and reliability. This is not a technical deficiency in AI methods but a structural feature of construction: projects are one-off, data ownership is distributed across a temporary coalition, and record-keeping conventions vary between firms and jurisdictions. The scale of the problem is measurable, a survey of 235 United States contractors found only 26% rating their data quality as high, with 58% describing it as merely moderate (Sobieraj and Metelski, 2026).

Generalisability follows directly. Because algorithms depend on context-specific training data, they resist transfer across project environments (Gao et al., 2026). A model trained on Jordanian building projects has no established validity for Nigerian road works. This is under-acknowledged in the literature, where models are frequently presented as general contributions on the basis of single-context validation.

Explainability has emerged as a distinct concern rather than a subsidiary one. The adoption of SHAP-based interpretation by Coffie and Cudjoe (2024) and the explicit framing of recent work around explainable AI (Chen et al., 2025) reflect recognition that in high-stakes environments, where inaccurate or opaque cost estimates produce budget overruns, delays and reputational risk (Chen et al., 2025), an unexplainable forecast is not actionable regardless of accuracy. A quantity surveyor cannot defend a figure to a client on the basis that a neural network produced it.

4.3.2 Organisational barriers

The organisational dimension is where the empirical evidence is densest and where the binding constraints appear to sit.

Skills deficits are near-universal and consistently rank first. RICS (2025) found lack of skilled personnel cited by 46% of respondents among their top three challenges, the single most frequent barrier reported globally. A systematic review spanning over 100 studies and some 36,269 firms confirmed skilled labour shortages as a widespread and geographically robust barrier (Sobieraj and Metelski, 2026). Osuizugbo et al. (2026), surveying 209 Nigerian construction professionals, found uneven digital competency with relatively stronger skills in data handling and BIM but significantly weaker proficiency in advanced AI capability and drew the important distinction between awareness, proficiency and application, noting that high awareness does not translate into strategic use. Sánchez et al. (2025), reviewing AI adoption in small and medium enterprises through a combined TOE–DOI lens, found that over 90% reported no AI applications in place, with knowledge gaps cited across 35 of the studies analysed.

Sobieraj and Metelski (2026) identify a self-reinforcing dynamic worth naming explicitly: labour shortages drive demand for automation, yet the same organisations lack the in-house expertise required to implement it, a cycle amplified by staff turnover and constrained margins. This is a competency-gap paradox rather than a simple deficit, and it implies that skills interventions must precede rather than accompany technology investment.

Cost operates as a compound barrier. Gao et al. (2026) identify hardware, software and technical expertise expenditure as a significant constraint, and the effect is regressive: firms most likely to benefit from productivity gains are least able to fund the transition. This connects to construction's fragmentation, where a long tail of small subcontractors lacks the balance sheet for capability investment.

Cultural resistance is more consistently reported in the developing-economy literature. Osuizugbo and Alabi (2022), conducting 47 stakeholder interviews in Nigeria, identified low awareness and acceptability, fear of unemployment, and cultural factors alongside finance and operational skills as barriers, while quality assurance, better planning, resource management, innovation, safety and on-time delivery emerged as drivers.

4.3.3 Environmental barriers

Rosenbaum & Bartels (2026), combining a survey of 159 construction professionals and students with expert interviews, found technological progress and societal expectations driving adoption while legal uncertainties, safety regulations and insufficient user knowledge constituted significant barriers. Liability allocation is genuinely unresolved: where an AI-generated schedule contributes to delay, or a vision system fails to detect a hazard preceding an accident, responsibility distribution between developer, deploying firm and supervising professional has no settled answer in most jurisdictions.

Privacy and worker consent arise specifically from safety applications. The use of surveillance cameras, location tracking and wearable devices raises data security and consent questions that may impede stakeholder acceptance (Gao et al., 2026). This creates a tension worth naming: the most operationally mature AI applications in construction are also the most intrusive, and their maturity may not survive contact with organised labour or strengthened privacy regulation.

Competitive pressure operates in the opposite direction. Katebi& Tehrani (2025) found competitive pressure a critical organisational-level determinant of behavioural intention, and Na et al. (2024), applying an extended UTAUT model, found facilitating conditions, social influence and competitive pressure all significant positive contributors to firm-level adoption.

4.3.4 Developing-economy contexts

Barrier profiles differ sufficiently between developed and developing economies that treating them as a single population obscures the mechanism.

In Nigeria, Ibrahim et al. (2026), applying TAM and organisational change management theory, found AI's potential for operational efficiency and decision-making recognised but adoption constrained by insufficient digital infrastructure and limited technical expertise. Osuizugbo and Alabi (2022) additionally identified electricity supply as a barrier, a constraint that simply does not appear in European or East Asian studies, and which is prior to any question of algorithmic sophistication.

The skills baseline is correspondingly thinner. Research across five Central African countries found that only 12–15% of regional construction professionals have BIM training and fewer than 3% report experience with integrated digital platforms, against a supply chain in which 30–50 subcontractors per project and informality rates of 60–70% are typical (BikoumouGambat et al., 2026). The same work notes that sub-Saharan Africa contributes under 2% of the relevant research literature despite substantial construction markets a knowledge asymmetry that risks interventions designed for conditions that do not obtain.

Adebowale and Agumba (2024) situate these constraints within a wider African skills and infrastructure context, and Sánchez et al. (2025) report parallel dynamics across small and medium enterprises more generally.

The analytical implication is that TOE's environmental dimension carries substantially more explanatory weight in developing economies than the technological dimension, inverting the emphasis of most Global North studies. Reviews that aggregate across contexts without stratification will systematically understate infrastructure and governance constraints.

4.3.5 The research–practice misalignment

The most striking recent evidence concerns not the barriers themselves but the literature's engagement with them. Sobieraj and Metelski (2026) analysed 4,668 construction AI publications from 1990 to 2025 and classified them against three practitioner-identified barrier dimensions, benchmarking research attention against the RICS (2025) practitioner survey. Table 7 reproduces the comparison.

Table 7: Research attention versus practitioner-identified adoption barriers (Sobieraj and Metelski, 2026)

Barrier dimension	Practitioner salience (RICS, 2025; n > 2,200)	Share of literature	Publications	Growth trend (R^2)	Composite attention score
Socio-technical (skills, culture, change management)	46%	4.6%	215	0.090	13 / 100
System integration (BIM, IoT, digital twin convergence)	37%	15.9%	742	0.654	62 / 100
Data integrity (quality, availability, governance)	30%	2.7%	125	0.189	17 / 100

The inversion is close to complete. The barrier practitioners report most often occupies the smallest and flattest share of the literature, while the dimension receiving the most sustained scholarly attention ranks second among practitioners. Expressed as practitioner-to-publication ratios, roughly 4.7 practitioners identify socio-technical barriers for every publication addressing them and 5.2 do so for data integrity, against 1.1 for system integration (Sobieraj and Metelski, 2026).

Two features of that analysis deserve emphasis because they resist easy dismissal. First, the misalignment is one of volume rather than quality: data-integrity and socio-technical publications receive citation attention broadly comparable to the field baseline, indicating that such work is not devalued once published but is initiated less often. This locates the problem in agenda-setting rather than gatekeeping. Second, the neglect is partial rather than absolute. Manual review of system-integration papers found 73% discussing data quality and 60% discussing organisational or workforce challenges, but on average across roughly half a page of a fifteen-page article. Sobieraj and Metelski (2026) characterise this as a specification problem: the foundational knowledge exists but is implicit, secondary and scattered, leaving practitioners unable to locate or operationalise it.

Their finding and the present review's converge, and the convergence is not coincidental. Both identify a literature optimising for what is technically tractable rather than what is practically binding. Where their analysis locates the bias in topic selection, the appraisal in Section 4.2 locates a further layer of the same bias inside the technical literature itself: even within the well-attended domains, the dominant output is accuracy improvement on retrospective data rather than evidence of deployed value. Technocentrism, on this reading, operates at two levelswhich problems get studied, and what counts as a solution.

4.4 Synthesis: reconciling performance with adoption

4.4.1 The accuracyadoption paradox

The two evidence streams synthesised above sit in apparent contradiction. Technical performance is high and improving. Adoption sits below 8% in Europe and below 1% for embedded organisational use globally. The obvious inference that practitioners are irrationally slow does not survive scrutiny.

A more defensible reading is that reported accuracy and managerial value have decoupled. A model achieving R^2 of 0.99 on 191 historical projects from one country tells a project manager in a different country,

International Journal of Latest Research in Engineering and Technology (IJLRET)
ISSN: 2454-5031
www.ijlret.com || Volume 12 - Issue 08 || August 2026 || PP. 01-20
DOI: 10.56581/IJLRET.12.07.01-20

on a different project type, very little. Its accuracy is real; its relevance is unestablished. Practitioners are responding rationally to a genuine evidential gap, not exhibiting resistance to change.

Three mechanisms sustain the decoupling:

a) **The validation mismatch.** Academic reward attaches to demonstrated accuracy on available data. Practical adoption requires demonstrated robustness on unseen data in live conditions. These are different tests, and the literature overwhelmingly performs the first as discussed earlier.
b) **The absorptive capacity constraint.** Deploying a cost prediction model requires structured historical cost data, staff able to interpret probabilistic output, and governance permitting decisions to be informed by it. Firms lacking these cannot capture value from even a perfect model. This explains why organisational barriers dominate technological ones in the empirical adoption literature (Section 4.3.2), and why the competency-gap paradox is self-reinforcing rather than self-correcting.
c) **The accountability gap.** Construction decisions carry legal and professional liability. Where responsibility for AI-informed decisions is unallocated (Section 4.3.3), rational managers will not act on model output regardless of confidence. Explainability is therefore not a technical nicety but an accountability precondition.

4.4.2 An integrated framework

Figure 2is integrated framework from AI capability to project performance

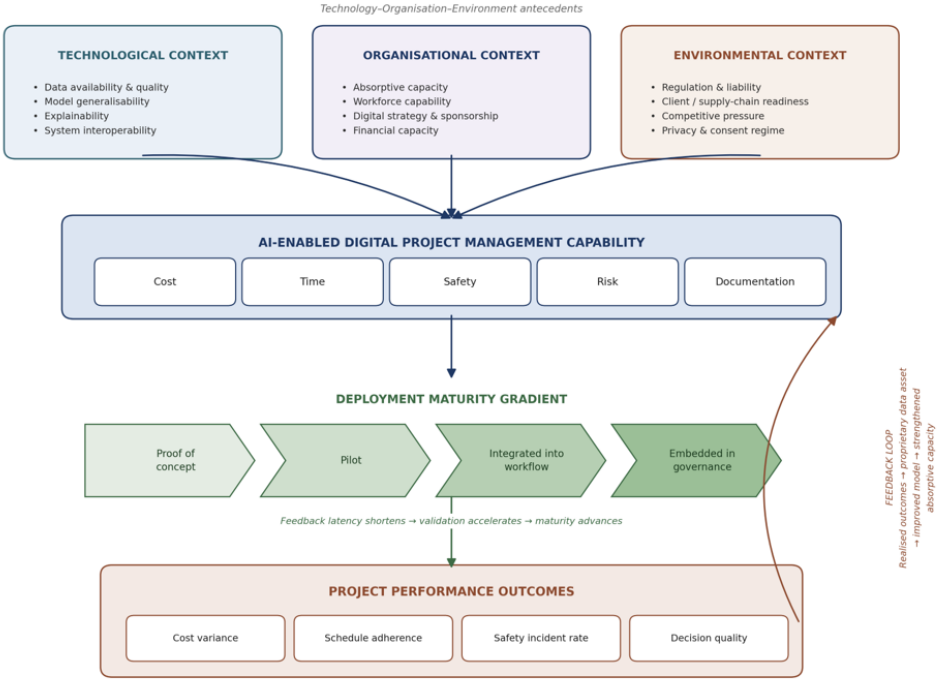

Figure 2: Integrated framework from AI capability to project performance (Tornatzky and Fleischer, 1990; Baghdadi, 2025; Gao et al., 2026).

The framework's central proposition is that technical capability is necessary but not sufficient. Value realisation is mediated by deployment maturity, which is in turn conditioned by organisational absorptive capacity and environmental permission. The feedback loop matters: firms that deploy generate proprietary data assets that improve subsequent models and deepen capability, producing cumulative advantage. This predicts divergence rather than convergence in industry AI capability, an empirically testable claim, and one with uncomfortable implications for smaller firms and developing-economy markets. The RICS (2025) distribution, in which widespread experimentation coexists with negligible embedded use, is consistent with a population overwhelmingly stalled at the pilot stage of that gradient.

4.4.3 Theoretical implications

First, the review demonstrates that TOE's relative dimensional weighting is context-contingent rather than fixed. In developed economies, technological and organisational factors dominate; in developing economies, environmental factors, infrastructure, power supply, regulatory absence become primary. TOE applications in construction should therefore report dimensional weighting rather than treating the three contexts as equivalent.

Second, the deployment-readiness asymmetry between safety and cost/time applications discussed earlier suggests that feedback latency deserves treatment as an adoption variable in its own right. Technologies producing rapid, verifiable ground truth will diffuse faster than those whose accuracy is confirmable only at project completion, independent of their technical quality or economic value. This is not, to the authors' knowledge, formalised in existing adoption theory.

Third, the accuracy–adoption paradox indicates that DOI's observability attribute operates differently for predictive technologies than for physical innovations. A prediction's correctness is observable only against a counterfactual that does not exist, the project as it would have run without the intervention. This structurally suppresses observability and may explain slower diffusion than relative advantage alone would predict.

Fourth, the research–practice misalignment documented by Sobieraj and Metelski (2026) suggests that socio-technical systems theory has been invoked more often than applied in this field. If adoption failures arise principally from misalignment between technical and social subsystems, then a literature devoting 4.6% of its output to socio-technical factors is not equipped to explain the phenomenon it studies.

4.4.4 Practical implications

For contracting and consulting firms, the sequencing implied by the framework is: data infrastructure before algorithms; capability before procurement; and pilot selection favouring short-feedback-cycle applications, which is why safety monitoring is a more sensible entry point than cost forecasting despite the latter's headline accuracy.

For clients and public agencies, procurement frameworks requiring structured digital project data would address the binding data constraint more effectively than mandating AI use directly. Clarifying liability allocation for AI-informed decisions would remove a barrier that firms cannot resolve individually.

For policymakers in developing economies, the evidence indicates that infrastructure and skills investment must precede technology promotion. Encouraging AI adoption where electricity supply is unreliable, BIM training reaches 12–15% of professionals and advanced proficiency is scarce (Osuizugbo and Alabi, 2022; Osuizugbo et al., 2026; BikoumouGambat et al., 2026) will produce symbolic rather than substantive uptake.

For the research community, the implication is a rebalancing rather than an expansion of effort. Sobieraj and Metelski (2026) call for research agendas addressing data governance frameworks, competency development and organisational change management; the present review adds that within technically oriented work, the marginal value of further accuracy improvement is now low relative to the value of external validation and deployment evidence.

5. Conclusion

This review set out to connect three questions usually treated separately: where AI is applied in construction project management, what it demonstrably achieves, and why adoption lags.

On application, AI now spans every major project management knowledge area, with cost estimation and prediction most heavily researched and safety monitoring most operationally mature. Technique selection has consolidated around ensemble methods and deep architectures for prediction, computer vision for site monitoring, and recently, an unevenly large language models for documentation and planning support.

On performance, the picture is less favourable than publication volume suggests. Reported accuracy is high but rests predominantly on retrospective validation, small geographically bounded datasets and inconsistently reported hold-out testing. Where hold-out performance is disclosed, degradation can be severe. Project-level outcome evidence, whether AI use improved cost, schedule or safety performance against a counterfactual is nearly absent from the peer-reviewed corpus.

On adoption, barriers cluster in the organisational domain, with data infrastructure, workforce capability, implementation cost and governance recurring across contexts. Environmental barriers dominate in developing economies, where infrastructure and regulatory constraints operate prior to any question of technical capability. And the literature itself is implicated: research attention is inversely correlated with practitioner-reported barrier salience, concentrating on system integration while the socio-technical and data-quality constraints practitioners actually encounter remain thinly and flatly researched.

The synthesis of these findings is the accuracy–adoption paradox, and this review's principal argument is that it is not a paradox at all. Predictive accuracy on historical single-context data is a weak signal of managerial value, and practitioners are responding proportionately to weak evidence. The field's dominant performance metric has outlived its usefulness as a proxy for practical worth.

The corrective is methodological rather than technical. Progress now depends less on architectural innovation than on validation discipline external validation across contexts, transparent hold-out reporting, and outcome studies measuring decision impact rather than prediction fidelity and on a rebalancing of research attention toward the foundational constraints that determine whether any of it can be deployed. Until the literature can demonstrate that AI-enabled digital project management improves projects rather than merely predicting them accurately, adoption will continue to lag capability. On present evidence, it is right to.

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ISSN: 2454-5031
www.ijlret.com || Volume 12 - Issue 08 || August 2026 || PP. 01-20
DOI: 10.56581/IJLRET.12.07.01-20

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