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Review Article

Exploring the Potential of Artificial Intelligence in Construction Project Management: A Narrative Review

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Abstract

The challenges of cost overruns, schedule delays, quality inconsistencies, and safety incidents in the construction environment pose a significant risk to successful project execution. This review explores how artificial intelligence and extended reality technologies are transforming construction processes and enhancing project outputs. This narrative review draws on peer-reviewed papers identified through targeted keyword searches in Scopus, Web of Science, Google Scholar, ResearchGate, and Academia, with relevance and quality judged informally by the author team based on their combined construction industry and academic research experience; no formal quality-appraisal instrument was applied and this review does not follow Preferred Reporting Items for Systematic Reviews and Meta-Analyses-type systematic-review reporting. Reported findings in the underlying literature indicate that machine learning models based on neural networks, support vector machines, and random forests can reduce forecast errors, and that dynamic scheduling tools and anomaly detection algorithms are associated with earlier detection of delays and emerging risks in the specific studies reviewed; these are presented as findings of particular studies rather than general established effects. The use of computer vision and thermal imaging enables defect detection and quality checks to be automated, while wearable sensors and predictive models enhance hazard detection and worker safety. Despite these opportunities, the review finds that implementation barriers are widely reported in developing-economy contexts, including Nigeria; the specific claim that these barriers have a comparatively greater impact than in other contexts is moderated here, as it was not directly evidenced. The review ends with a call for better empirical study, better understanding between practitioners and technologists, better data governance and bias auditing, and better policy support to ensure that these tools are widely accessible, not just within well-resourced firms.

Categories: AI Adoption Barriers and Facilitators, Practitioner-AI Collaboration in Applied Research, Workflow and Productivity Impacts of AI

Keywords: ai potential, project management, augmented reality (ar), construction, extended reality

Introduction And Background

In recent years, the use of Artificial Intelligence (AI) in the construction industry has grown significantly because of the demand to improve productivity, optimize project performance, and reduce risks, cost overruns, schedule delays, safety issues, and resource inefficiencies. As AI becomes increasingly prevalent, it is transforming project management and the

way construction professionals approach project risks, cost management, activity scheduling, and resource allocation. AI systems can use machine learning (ML) and deep learning algorithms to identify patterns and generate insights from various project datasets that go beyond what can be done through traditional analytical approaches, such as historical costs, schedules, resource allocation, and real-time site data [1,2].

Despite these numerous benefits and opportunities, the sector continues to face persistent challenges such as projects often overrunning budgets, schedules slipping, quality issues after work completion, and worker-safety incidents [3,4]. These challenges arise from a range of interacting factors-contractual, financial, regulatory, organizational, supply-chain, design-related, and site-specific, among which inadequate early identification of potential threats, fragmented information systems, and decision-making that leans on expert opinion rather than real-time project data are commonly cited contributors [3,4]. One of the most persistent and costly problems in the construction sector is construction cost overrun, which costs billions of dollars worldwide. The issue is especially acute in developing countries like Nigeria, where budgetary deviations are often worsened by economic volatility, disruptions in the supply chain, poor infrastructure, and project management issues [3,5].

The key strengths of AI in construction lie in its ability to fill these gaps by leveraging historical project data and real-time variables to provide accurate forecasting of material costs, labor productivity, and project costs; automated risk identification using pattern recognition in project documentation; early warning systems that identify projects that are beginning to fall behind on schedule or budget; and intelligent resource optimization that matches the availability of labor, equipment, and materials with the project requirements [2]. In addition to operational efficiencies, AI can be leveraged for quality assurance by analyzing construction progress through images, monitoring compliance, and detecting defects, as well as for safety measures, such as integrating wearable technology, developing hazard prediction models, and creating immersive training environments [6,7].

Currently, the use of AI in the construction industry is still in its relative infancy, particularly in developing countries, which limits the possibilities of utilizing it more fully. Evidence from quantity surveying practice more broadly suggests that technology adoption in QS firms is held back by a lack of technical expertise and the cost of implementation [8]. Nigeria-specific survey evidence corroborates this: a 2026 survey of 426 construction professionals in Imo State, Nigeria, spanning project managers, engineers, architects, and quantity surveyors found generally low awareness and adoption of AI technologies (including ML and predictive analytics relevant to cost and schedule management), with small and medium-sized enterprises, which make up close to 90% of the surveyed Nigerian construction sector, facing particular resource constraints [9].

This review was conducted to study the various studies on the use of artificial intelligence in construction project management, its potential, and the various challenges that prevent the extensive use of AI in the construction sector. This study will incorporate existing research and evidence to inform construction professionals, researchers, educators, and policymakers about trends in project management with the use of AI, direct evidence-based use of these innovations, and identify key research gaps and policy needs to help move the field forward in a multitude of global construction contexts.

Previous reviews have explored AI applications in construction project management generally [2] and AI together with building information modeling for sustainable construction, based on a cross-sectional survey of construction companies in Slovakia, Slovenia, and Croatia [7]. Relative to these, this narrative review contributes a synthesis that (a) treats AI and augmented reality/extended reality (AR/XR) as a single, function-linked technology set rather than reviewing them in isolation, and (b) centers the adoption barriers and equity implications of AI/AR use for construction firms in developing economies, using Nigeria as an illustrative case, a lens that is largely absent from the reviews cited above.

Review

The narrative review method was chosen for this paper because it is suitable for a broad, interpretive synthesis of a rapidly evolving, cross-disciplinary area like the application of AI in the construction project management process, in which the objective is to summarize recent applications, challenges, and directions for practitioners and policymakers,

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rather than quantitatively pool effect sizes from a limited number of studies. For this reason, a narrative approach was selected instead of a systematic or scoping protocol, and no claim is made for Preferred Reporting Items for Systematic Reviews and Meta-Analyses-type reporting.

As in this approach, targeted searching was performed in scholarly databases (Scopus, Web of Science, Google Scholar, ResearchGate, and Academia) whose journal coverage has been comparatively examined in the bibliometric literature [10] using the keywords "artificial intelligence," "machine learning," "construction project management," "cost management," "schedule optimization," "risk prediction," "cost overrun," "schedule delay," "project performance," "decision support system," and "automation in construction," combined with Boolean operators. AR/XR-related literature was identified through citation snowballing from the retrieved AI-focused papers and the authors' existing familiarity with the AR/BIM construction literature, rather than through direct keyword search of "augmented reality," "extended reality," or "virtual reality" in the primary databases. This is a limitation of the search strategy, acknowledged further in Future Directions. The search terms were not predetermined but were built up and adjusted as the review proceeded, following the methodology of narrative review; this approach does not allow for rerunning of the search to generate the same result.

Articles and peer-reviewed conference proceedings in English were prioritized; two non-peer-reviewed sources (a preprint and an arXiv manuscript) were retained where no peer-reviewed equivalent addressing the same specific application (early-warning schedule-deviation systems; AI-wearable fatigue monitoring) was identified during the search period and are flagged as such throughout. Papers on either the use of or effectiveness of AI, or the potential of use of AI for construction project management, were accepted, while papers concerned with other domains were not.

Relevance and quality were judged informally against three criteria applied consistently by the author team: (i) direct relevance to one of the six functional domains reviewed (cost, schedule, risk, quality, safety, resources); (ii) whether the study reported an application, evaluation, or empirical test of an AI/AR technique, as opposed to purely conceptual discussion; and (iii) recency and venue credibility (peer-reviewed journal or conference proceeding). No inter-rater reliability statistic was calculated for this narrative review. The Newcastle-Ottawa Scale and Technology Readiness Index were not used as formal scoring systems generating quantitative appraisal scores, since this is a narrative rather than a systematic review.

In cases where the maturity of a specific AI application is described in the text (e.g., proof-of-concept versus field-deployed), these descriptions are based on the qualitative reading of the source by the author team and not on a standardized appraisal score. These categories were assigned as follows: field-deployed: the source reports use on live construction projects with production data; pilot: the source reports a limited-scale trial on a real project or with practitioner participants, without an indication of ongoing production use; proof-of-concept: the source reports a technique tested only in a laboratory, simulated, or synthetic-data setting. The assignment was made by the author team's qualitative reading of each source's stated methodology and was not independently verified by a second rater.

A summary of a representative sample of studies discussed in this review is provided in Table *1*. The table is not intended to present a systematic and comprehensive catalogue of methods and evidentiary strength in the literature; it is rather intended to show the range of methods and evidentiary strength in the literature.

Current applications of AI in construction project management

Cost Prediction and Management

The development of cost predictive models is one of the most noticeable developments in AI for construction project management. ML algorithms (including artificial neural networks (ANNs), support vector machines (SVMs), random forest, and gradient boosted models) have been trained using historical project data for various cost components (materials, labor, equipment, subcontractors), project characteristics (scope, location, type of client), and contextual variables (inflation, disruptions in the supply chain, changes in regulations), thereby predicting project final costs with a higher level of accuracy than traditional project estimating techniques [11]. Torres et al. [12] report that AI-driven

assistants are perceived by academic and industry practitioners as enhancing several project-management competencies, including aspects of cost-related decision-making, though this reflects a perception-based dual academia-industry survey rather than a direct comparative accuracy test.

They are used at different stages of the project, including conceptual estimating and detailed design [11,13]. For instance, AI-driven cost management software can process project invoices and track costs against forecasts, alerting project managers to variance thresholds; current evidence indicates this remains a largely under-deployed capability in practice, particularly at tendering and construction stages, rather than routine operational use [14]. Additionally, natural language processing (NLP) algorithms have been used to automatically extract cost-relevant information from unstructured project documents. Jafari et al. [15] demonstrate this specifically for contractual reporting requirements, estimating the associated reporting time and cost, rather than for site-meeting minutes or stakeholder correspondence, which remain plausible but as-yet-undemonstrated extensions.

Schedule Optimization and Delay Prediction

Delay is one of the most critical contributors to project failures in construction [4,16]. Egwim [17] developed ML delay-prediction models and compared performance across several ensemble and individual ML algorithms, reporting that ensemble methods outperformed individual algorithms; this study does not benchmark ML prediction against traditional critical-path or risk-weighted duration-estimation methods, so the comparative claim should be read as a research gap rather than an established finding.

More advanced uses involve dynamic scheduling. Hsieh et al. [18] demonstrate a system that uses surveillance-camera images and AI-based object detection, integrated with BIM, to compare detected construction progress against the planned schedule. This differs from a fully closed-loop, real-time critical-path recalculation system: the demonstrated capability is automated progress-vs-plan comparison rather than dynamic reallocation or continuous critical-path recomputation from wearable-sensor or GPS data. Realizing the latter, a more ambitious closed-loop vision remains an area for further development.

Identification and Early Warning Systems for Risk

AI-driven early warning systems are an emerging area of construction risk management. Kumar and Shrivas et al. [19] (a preprint) review the literature on AI-based early-warning systems for schedule deviations specifically, rather than broader unsupervised clustering/anomaly-detection applications across cost, quality, and productivity indicators; the latter represents a plausible extension of the reviewed literature rather than a directly demonstrated capability. These systems could draw on a variety of data sources such as project management information systems (cost and schedule data), supply chain monitoring, workforce analytics, weather data, and site conditions. Taresh et al. [20] use questionnaire data and statistical analysis (not ML models) to examine relationships between information-systems use, project risk management, and project-management success in construction companies, reporting that better information-systems use is associated with improved risk-management outcomes; this supports the general premise that better data/information flow aids risk management but does not itself demonstrate ML-based prediction of project failure from past outcomes.

Defect Detection and Quality Control

Manual inspections are time-consuming and subjective. Convolutional neural networks (CNNs) applied to progress and thermal images have been used more broadly for construction and infrastructure defect recognition [21,22]; the specific application to concrete finishes, rebar placement, and joint quality, and the reported sensitivity/specificity levels, would benefit from direct supporting studies and are presented here as illustrative rather than established for these exact defect categories. In particular, computer-vision methods of this kind can, in principle, be used in high-volume, repetitive quality checks (e.g., thousands of concrete samples, masonry work on large facades).

Mirzabeigi et al. [23] demonstrate automated detection of building-envelope thermal anomalies, including thermal bridges and air-leakage paths, primarily for post-construction building inspection and retrofit assessment. Extending this capability to pre-completion, construction-stage detection of insulation gaps and moisture intrusion, and the associated

avoidance of post-occupancy litigation costs, is a plausible application that has not yet been directly demonstrated in the cited evidence.

Worker Safety and Hazard Prediction

AI plays a key role in construction safety by detecting hazards, predicting incidents, and improving training. Wearable sensors like accelerometers, gyroscopes, and GPS can enable real-time detection of unsafe work practices. This includes falls, improper equipment handling, and proximity to hazards [24]. To keep construction sites safe, computer vision systems identify unsafe behaviors. This includes spotting workers without the right personal protective equipment (PPE), unsafe scaffolding setups, and machinery operating in areas where people are present. These systems provide real-time alerts to site supervisors [25]. Predictive safety models use historical incident data and site conditions to forecast hazard risk levels for specific activities and site layouts, helping to direct safety measures and resource allocation [24]. These systems are particularly helpful in scenarios with a lot of information, like large, complex projects, where the subtle patterns that lead to incidents might not be obvious to human safety managers.

Resource Optimization and Supply Chain Management

Linear programming and optimization algorithms offer solutions to resource-allocation problems such as labor-crew scheduling and equipment-plan sequencing in repetitive construction activities, aiming to reduce cost while meeting schedule constraints [26]. Extending these models to material procurement scheduling and quality constraints is a further application area not directly evidenced by the cited study. Supply chain optimization models more broadly can anticipate a disruption in the supply of materials, suggest inventory strategies, and recommend alternative supplier sourcing to reduce supply chain risk.

The current applications of AR and XR in the construction sector

Site Visualization and Coordination

AR is used to superimpose virtual construction models onto construction sites. Nassereddine et al. [27] identify clash detection, construction-progress visualization, and client-facing virtual tours as established AR use cases in the reviewed literature; direct comparison of as-built conditions against design intent and a demonstrated reduction in change orders from expectation misalignment are plausible extensions of these use cases rather than findings directly reported in the study [27].

Safety Training and Worker Education

Immersive Virtual Reality (VR) training environments provide repeatable practice of high-risk construction activities such as machinery operation and site hazards [28]; AR-specific training, confined-space entry, and hazardous-materials handling are related but not directly evidenced applications in the cited source. Carvalho et al. [29] support general benefits of VR for learning and skills development but do not establish greater learning rates or substantially fewer real-world errors compared with traditional classroom or onsite training; the review itself notes that evidence on real-world skill transfer and long-term outcomes remains limited.

AI vs. AR in Construction: A Comparative Investigation

AI and AR work together in construction project management; they support each other. AI excels at analyzing large sets of project data. It can find patterns, make predictions, and help with decision-making. On the other hand, AR improves spatial visualization. It helps with clear communication among stakeholders and makes information easy to access on the job site. Combining these strengths suggests a plausible integrated workflow: AI analytics of site conditions and design models could recommend construction-task sequencing, displayed to on-site teams via AR for real-time feedback and adjustment; similarly, AI-generated clash-detection models or computer-vision defect flags could in principle be visualized through AR annotations on site. We present this as a conceptual synthesis rather than a demonstrated integration; the AI and AR capabilities reviewed above [12,30] are, to date, largely evidenced as separate applications, and directly evidenced combined AI-AR workflows of this kind were not identified in the literature reviewed.

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Comparative Appraisal

Comparing across the domains reviewed above, the following patterns emerge. First, the most consistently reported performance improvements from AI techniques, such as cost prediction (ANNs, SVMs, random forest) and defect detection (CNNs on labeled images), rely on well-structured, quantitative training data, and that is because structured cost records from history and labeled image datasets are much more commonly available than, say, standardized risk data and safety data. Second, methods for less-structured problems, like early warning risk detection or multimodal root-cause analysis, are reported with less methodological detail in the sources reviewed and are more dependent on vendor field trials than on independent field trials.

Third, cost/schedule-oriented applications appear to have more field deployments referenced in this review's own source set than safety-oriented applications, most of which are represented here at the proof-of-concept or pilot stage. We note, however, that this maturity assessment is a characterization of the specific sources sampled in this narrative review's own search, not a comprehensive appraisal of the safety-AI literature as a whole: Gao et al. [11], a systematic review with broader coverage than the present study, reports that safety-related AI applications are, if anything, closer to deployment than several cost- and time-related applications, which remain concentrated at validation and pilot stages. We flag this discrepancy explicitly rather than resolving it and treat our maturity ranking below as provisional and specific to the studies discussed.

Methodologically, the studies underlying this review vary widely in rigor, from reporting controlled comparisons to traditional methods (e.g., ML cost models compared to traditional estimating) to descriptions of vendors' case studies that provide no comparison group or independent verification, a limitation previously mentioned in the Future Directions section.

One tension worth noting explicitly: this review's own discussion of algorithmic bias (see Challenges and Ethical Issues section) illustrates, hypothetically, how AI-driven contractor-exclusion or procurement decisions could occur; this is in tension with the later discussion of automation bias, which warns against unchecked reliance on such automated decisions. We present this as an internal tension in the implications discussed in this review, not as a documented contradiction within the empirical studies cited, as no specific published study of algorithmic contractor exclusion or automated procurement decision-making was identified in our search, and this is itself an evidence gap.

For construction project managers, the takeaway is that decisions to implement AI should be prioritized based on the maturity of the evidence available for the specific application under consideration: cost and schedule tools have, in the sources reviewed here, the greatest amount of evidence and are reasonable to pilot-test in the near term with independent verification; safety and risk tools have a smaller amount of evidence in this review's sample (though see the caveat above regarding [11]) and should be pilot-tested with human oversight; and equity-oriented tools have the least evidence and should be treated as a research priority rather than a procurement priority at this point.

Challenges and Ethical Issues

While AI and AR offer promising opportunities for reforming construction project management, they also present substantial challenges for adoption and raise ethical and practical issues that demand careful and cognizant measures to mitigate.

Data Availability, Quality, and Standardization

To be effective, ML models must be trained on sizable, representative, high-quality datasets. Large volumes of project data are kept on file by construction companies, but they are dispersed across numerous systems, such as project management software for schedule data, accounting systems for cost data, inspection reports for quality data, and incident reporting systems for safety data. A comprehensive understanding of project performance is hindered by data silos and a lack of a uniform definition and format for data across enterprises, which makes it challenging to compare and generalize models. This pattern of data fragmentation is a general challenge in heterogeneous data-integration contexts [31], applied here illustratively to the construction-industry setting rather than as a construction-specific empirical finding. Furthermore, biases related to previous relationships, behaviors, and decision-making are frequently present in

historical project data. These biases can be reinforced by algorithms that are trained on this data, leading to incorrect classifications. For instance, the model will consistently overestimate the costs for specific subcontractor companies if the historical cost overruns are restricted to them due to past relationship issues rather than skill disparities. This can lead to self-fulfilling predictions, such as when these companies are excluded from competitive bids due to biased model output [32].

Cyber Security and Data Privacy

Sensitive construction data is essential for AI systems, such as detailed cost breakdowns showing the firm's financial strategies, schedule information showing productivity metrics and work methods, and labor data containing personal information about workers. Unauthorized access to such data allows for the abuse of competitive intelligence, theft of intellectual property, and worker surveillance. Construction companies often face the challenge of having insufficient cybersecurity infrastructure to safeguard real-time AI systems, especially small and medium-sized enterprises, for which cybersecurity resource and infrastructure constraints are a documented general concern [33]. However, the cited study focuses on cybersecurity threats and defensive strategies for small and medium-sized firms generally and does not provide direct evidence of infrastructure deficits in construction firms specifically. Compliance with regulatory requirements for data protection [General Data Protection Regulation (GDPR) in Europe and sector-specific regulations elsewhere] increases complexity and cost, especially for companies with operations in several jurisdictions.

Algorithmic Bias and Fairness

Historical project information may be used to create ML models that systematically exclude certain populations or types of organizations. ML systems can reproduce and reinforce historical bias present in their training data [32]. Applied illustratively to construction: cost prediction models trained mostly on well-resourced projects in developed economies could, in principle, systematically overestimate the cost of small firms or small projects in developing economies, making them less competitive to enter the market; a construction-specific empirical study of this scenario was not identified in our search. Likewise, we hypothesize that models developed to predict schedules based on traditional delivery methods could, if deployed uncritically, discourage adoption of innovative delivery methods by systematically flagging them as higher-risk, though we did not identify a construction-specific empirical study testing this mechanism, and it is presented here as a plausible risk rather than a documented finding. Risk identification algorithms can be biased and exclude certain subcontractor firms or types of labor from future work due to the historical assessment of their performance.

What Does It Cost, and What Is the Equity Impact of Implementation?

There is a high initial cost for implementing AI and AR systems, including the investment in technology infrastructure, data collection, employee training, and organizational changes. While large and multinational construction companies may be able to cover these expenses and hire specialized AI experts, smaller companies and those in developing economies may have difficulties, a pattern documented for AI adoption barriers among manufacturing SMEs in Pakistan [34], presented here as analogous, adjacent-sector evidence rather than construction- or AR-specific data. This could widen the capability gap between market leaders who exploit the competitive advantage of AI and smaller companies that face difficulties competing; the specific consequence of industry concentration toward larger companies and a decrease in diversity and innovation is presented here as a potential risk rather than an empirically demonstrated outcome.

Over-Reliance and Automation Bias

The "automation bias" effect, in which people over-rely on algorithmic recommendations, particularly under time pressure or cognitive load, is discussed in the human-AI interaction literature. Bertoncini et al. [35] examine this using an large language model-based synthetic simulation of decision-making rather than observed human participants and do not specifically isolate time constraints or cognitive exhaustion as moderating conditions; we treat the general automation-bias concern as well-established in the broader human-factors literature, while noting that study [35] itself provides a synthetic rather than human-subject evidence base.

Applied hypothetically to construction: high-stakes decisions such as awarding multimillion-dollar contracts, approving significant change orders, or allocating safety resources could be vulnerable to this effect if human oversight and professional judgment are insufficient. An AI recommendation to exclude a long-standing, reliable subcontractor based on skewed past-performance reviews, or to defer important safety investment on cost-optimization grounds, illustrates the kind of consequence this risk implies; these are presented as illustrative scenarios, not documented incidents.

Preserving professional judgment and critical scrutiny in the face of automated recommendations is widely recommended in the human-AI collaboration literature. Deliu and Moldovan [36] discuss preserving human interpretive agency and the ability to challenge algorithmic outputs, and we draw on this general framework in proposing that system design, user education on algorithmic limitations, and organizational culture together support genuinely supportive (rather than substitutive) AI use.

Regulatory and Ethical Frameworks

The construction industry's AI regulatory environment remains, in our reading, sector-underdeveloped rather than wholly absent. General data-protection instruments such as the EU GDPR and, relevant to the Nigerian context, the Nigeria Data Protection Act 2023, already govern personal data (e.g., worker biometric, location, and productivity data) collected by construction AI and wearable systems, and the EU Artificial Intelligence Act establishes general obligations around transparency and human oversight for AI systems. What remains unclear, in our assessment, is construction-sector-specific guidance on algorithmic accountability, interpretability, and liability attribution when an algorithmic decision contributes to project failure or worker harm, a gap in sectoral specificity rather than a gap in applicable law as such.

This ambiguity, arising from the fragmented legal duty for project performance across numerous parties (owners, contractors, consultants, and subcontractors), creates uncertainty in responsibility allocation for algorithmic errors [37]. For the construction industry, regulators must develop special frameworks that include bias testing and monitoring protocols, algorithmic transparency and auditability (explainability of the algorithm's recommendations), and liability attribution in the event of algorithmic failures.

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AI/AR Technique	Construction PM Domain	Key Finding	Author
ANN, SVM, random forest, gradient boosting	Cost prediction	Higher-accuracy final cost prediction than traditional estimating techniques: perception survey, not an accuracy test	Gao et al. [11]; Zhang [13]
AI-driven cost management software	Cost management	Limited practical deployment reported, particularly at tendering/construction stages: not a demonstrated real-time invoice/timesheet system	Ayinla et al. [14]
NLP	Cost data extraction	Automated extraction of cost-relevant data from contractual reporting requirements specifically (not meeting minutes/correspondence)	Jafari et al. [15]
ML delay-prediction models	Schedule delay prediction	Ensemble ML outperforms individual ML algorithms; NOT benchmarked against critical-path/risk-weighted methods	Egwim [17]
Camera-based AI progress monitoring + BIM	Schedule management	Automated comparison of image-detected progress vs. plan; does NOT demonstrate sensor/GPS data use or real-time critical-path recalculation	Hsieh et al. [18]
Early-warning review (schedule focus); IS-success survey	Risk identification	Reviews schedule-deviation early warning specifically, not broad clustering/anomaly detection	Kumar and Shrivas et al. [19]; Taresh et al. [20]
CNN/computer vision	Defect detection & QC	Recognition of quality deviations in progress/thermal images (general); concrete/rebar/joint specifics and sensitivity/specificity figures flagged as illustrative, not directly evidenced	Jiang and Messner [21]; Mohammadi et al. [22]
Thermal imaging + AI	Building envelope inspection/retrofit	Detection of thermal bridges/air leakage for POST-CONSTRUCTION inspection and retrofit; NOT demonstrated pre-	Mirzabeigi et al. [23]

		completion/moisture/litigation -cost avoidance	
Wearable sensors, computer vision	Worker safety	Real-time detection of unsafe behavior, PPE non-compliance, hazard proximity	Onososen and Musonda [24]; Li et al. [25]
Linear programming/optimization	Resource optimization (labor/equipment)	Reduced cost while meeting schedule constraints in labor-crew and equipment-plan scheduling	Garcia Nieves and Ponz-Tienda [26]
AR	Site visualization and coordination	Clash detection, progress visualization, client virtual tours established; as-built-vs-design-intent comparison and change-order reduction are plausible extensions, not directly evidenced	Nassereddine et al. [27]
VR (training)	Safety training	Supports learning/skills development; comparative learning-rate/error claims vs. classroom training	Xu and Zheng [28]; Carvalho et al. [29]
Digital twin	Pre-construction optimization	Virtual replica reduces trial-and-error via continuous real-time updating	Nguyen and Adhikari [38]; Kookalani et al. [39]
Generative AI; AI-blockchain (prospective)	Multi-party collaboration	discusses prospective generative-AI applications; evaluates AI-blockchain alert validation	Ghimire et al. [40]; Goundar and Gondal [41]
AI-powered wearables	Worker wellness (fatigue)	Detection of fatigue-related risk signs	Kakhi et al. [42]
Teleoperated robotics + AR (not AI-enhanced monitoring)	Remote inspection	Live video + AR comparison of as-built vs. BIM model via teleoperated quadruped robot	Halder et al. [43]
Multimodal AI (text, sensor time-series) — smart-city context	Root-cause analysis (prospective extrapolation)	integrates text + traffic-sensor time-series for SMART-CITY congestion prediction; construction root-cause application is this review's own proposed extrapolation	Alkhater [44]

TABLE 1: Synopsis of representative studies included in this review

Note: Linear programming/optimization is included as an algorithmic (non-AI/ML) resource-optimization method relevant to this review's broader AI/AR-adjacent scope. ANN, Artificial Neural Network; AR, Augmented Reality; CNN, Convolutional Neural Network; ML, Machine Learning; NLP, Natural Language Processing; QC, Quality Control; SVM, Support Vector Machine; VR, Virtual Reality

Future Directions

Although AI and AR have a lot of potential for construction project management, there are still a lot of research and implementation issues that need to be resolved. Proof-of-concept research, small-scale deployments, and vendor-published case studies with little independent verification make up a substantial part of this review's own source set, particularly for safety-related applications in the specific studies we identified. However, we note that this characterization should be read in the context of the broader systematic review's findings [11], which suggest that safety applications may, in fact, be relatively advanced (see the Comparative Appraisal section). Many studies lack long-term follow-up and comparison groups and do not take organizational transformation and implementation costs into account. The present review must also be interpreted with a related limitation: the iterative, expert-judgment-based process of searching and selecting the literature is not designed to be independently reproducible, and future efforts aggregating and summarizing this literature will benefit from using a systematic or scoping review protocol with a fixed, reportable search strategy, including a direct AR/XR keyword search to complement the interpretive breadth of the present review.

To determine whether using AI for project management actually improves construction outcomes (cost control, schedule performance, quality, and safety) when compared to traditional project management, and whether the advantages of such use are maintained over time as construction organizations and technology vendors change, the field needs to be advanced through larger, longer-term empirical studies across a wider range of construction contexts.

Innovative frontier applications require smart investment in research. In order to minimize trial-and-error approaches, construction methodologies could be optimized prior to construction by using a digital twin, a highly detailed virtual replica of constructed assets that is continuously updated with real-time sensor data and operated in parallel with the actual construction [38,39].

The combination of blockchain, generative AI, and AI/AR technologies has been proposed as a means to improve trust and transparency in multi-party construction collaborations. Ghimire et al. [40] discuss the potential (prospective, not yet demonstrated) applications of generative AI in construction, including text-based document processes. Goundar and Gondal [41] evaluate an AI-blockchain system in which smart contracts validate and log AI-generated cybersecurity alerts: a data-security application, not a demonstrated payment- or schedule-automation system. We present the extension of these two capabilities toward automated construction payments and schedule decisions as a prospective possibility, not a finding reported in either source.

Policy and capacity-building efforts are critical to equitable AI adoption. Governments in developing economies should create public-private partnerships to create open-source, sector-specific AI tools (cost prediction models trained on regional projects, risk identification systems reflecting regional hazards) that can be accessed by smaller companies and public agencies at low cost. Professional organizations (quantity surveying associations, project management institutes, amongst others) should develop certification and continuing education courses to ensure that practitioners are aware of the capabilities and limitations of AI, are able to review AI recommendations for bias and error, and have the ability to exercise professional judgment alongside AI. Research institutions need to focus on creating AI tools and training specifically for the construction environment in developing economies, rather than simply transferring tools that were developed in the construction markets of wealthier countries.

International cooperation between researchers, regulators, and industry organizations can accelerate the development of global standards for AI in construction. This includes the creation of data standardization for comparative analysis, algorithmic audit protocols to confirm model accuracy and fairness, and liability and regulatory frameworks to guarantee

safe deployment and preserve innovation incentives.

Scalable innovations are beginning to appear in the short term that need applied research and piloting. An AI-powered wearable device that identifies fatigue-related risk signs in construction workers has been proposed as a way to support preemptive wellness interventions; Kakhi et al. [42] evidence fatigue-detection capability specifically, rather than the broader combination of productivity change and early-illness detection previously implied. AR environments combined with live camera feeds and BIM comparison support remote construction-progress oversight without continuous on-site presence; Halder et al. [43] demonstrate this using a teleoperated quadruped robot with live video and AR-based comparison to the BIM model, rather than AI-enhanced progress monitoring or virtual team management as such, and the framework does not establish a reduction in overall project-management expenses. AI can also be integrated into the supply chain forecasting process to predict material changes, offer alternative materials, and suggest flexible procurement plans to keep to the schedule and cost while facing supply chain fluctuations.

Multimodal AI, combining text, image, time-series, and network data, has been explored for smart-city applications; Alkhater [44] integrates textual reports and traffic-sensor time-series data for smart-city congestion prediction. We propose, as a future direction rather than a demonstrated capability, that an analogous multimodal approach combining project correspondence, site imagery, performance time-series, and organizational-network data could support root-cause analysis of construction project failure: this is our own extrapolation, not a finding of the study [44]. If realized, such systems could in principle help detect multiple and complicated causes of project failure and suggest interventions addressing root causes rather than symptoms (Table *2*).

AI/AR Technique	Construction PM Domain	Key Finding	Author
Digital twin	Pre-construction optimization	Virtual replica reduces trial-and-error via continuous real-time updating	Nguyen and Adhikari [38]; Kookalani et al. [39]
Generative AI; AI-blockchain (prospective)	Multi-party collaboration	prospective generative-AI document support. AI-blockchain data-security/alert validation	Ghimire et al. [40]; Goundar and Gondal [41]
AI-powered wearables	Worker wellness (fatigue, not illness)	Detection of fatigue-related risk signs	Kakhi et al. [42]
Teleoperated robotics + AR	Remote inspection	Live video + AR comparison of as-built vs. BIM via teleoperated quadruped robot; label changed from "AR + AI progress monitoring"	Halder et al. [43]
Multimodal AI (text, sensor time-series) — smart-city origin	Root-cause failure analysis (prospective extrapolation)	Original study fuses text + traffic-sensor data for smart-city congestion prediction	Alkhater [44]

TABLE 2: Synopsis of representative studies on emerging and frontier applications discussed in Future Directions

AI, Artificial Intelligence; AR, Augmented Reality; BIM, Building Information Modeling; PM, Project Management

Conclusions

The transformative potential of AI and AR technologies in construction project management is highlighted in this narrative review, which offers unmatched opportunities to anticipate project risks early, accurately forecast project costs and schedules, optimize resource utilization, and improve worker safety and quality outcomes. These are described as opportunities rather than demonstrated outcomes: as discussed under Comparative Appraisal and Future Directions section, much of the underlying evidence remains conceptual, proof-of-concept, or vendor-reported, and independently verified, comparative field studies are still needed before these gains can be claimed as established. However, if this potential is to be realized, it is crucial to concentrate on major implementation challenges and ethical consequences. Data standardization, availability, and quality remain significant obstacles, particularly in developing-nation building settings. Proactive steps must be taken to address algorithmic bias, cybersecurity risks, and equity concerns in order to minimize any potential negative effects of AI use and guarantee that it promotes diversity and justice in the sector. System designs must guarantee that human judgment and decision authority are maintained because relying too much on algorithmic recommendations could jeopardize professional judgment and accountability.

We urge the following to guarantee the fair, efficient, and morally sound integration of AI and AR in building project management: (i) researchers should conduct more thorough and comprehensive empirical research to determine actual performance gains, implementation costs, and organizational changes required to adopt AI in construction in developing economies; (ii) construction practitioners and firms should encourage responsible adoption, including the need to use professional judgment and critical thinking when evaluating algorithm recommendations, to invest in staff training and change management, and to create organizational cultures that view AI as a tool to supplement rather than replace human expertise; (iii) regulatory bodies and professional associations should create standards for transparency, bias, cybersecurity, and liability attribution that are clear and in line with technological advancements, including construction-sector-specific guidance building on existing general data protection and AI instruments (see Regulatory and Ethical Frameworks section); and (iv) policymakers should assist in establishing infrastructure, capacity, and public-private partnerships for the equitable adoption of AI across a range of scales and locations, including developing economies. Building on the evidence gaps identified in the Comparative Appraisal and Future Directions sections above, three research priorities follow directly: (i) independently verified, comparative field studies of AI cost and schedule tools against traditional methods on matched projects to move beyond vendor-reported figures; (ii) longitudinal safety-outcome studies of wearable-sensor and computer-vision hazard detection, since current evidence in this review's own sample is dominated by short-term proof-of-concept deployments; and (iii) adoption-cost and return-on-investment studies specific to small and developing-economy contracting firms, to test whether the equity concerns raised in this review are borne out empirically or can be mitigated through the open-source, sector-specific tooling proposed above.

Additional Information

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All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

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AI Disclosure Statement

The authors used ChatGPT (GPT-5.5, OpenAI) and Claude 3 to assist in identifying relevant search terms and suggesting potentially relevant publications during the preliminary literature search. The suggested information was independently verified by the authors, and all literature included in this narrative review was identified, retrieved, screened, and evaluated through searches of scholarly databases, including Scopus and Google Scholar. The AI tool was not used to generate research findings, analyze data, or formulate the review's conclusions. The authors take full responsibility for the content, interpretation, and accuracy of the manuscript.

Data Availability Statements

Data sharing is not applicable. This work is theoretical; no datasets were generated or analyzed.

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