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Artificial Intelligence in Construction Practice: Applications, Benefits, Challenges, and Future Directions

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***Abstract*—The construction industry is turning to artificial intelligence (AI) to address persistent problems of schedule delay, cost uncertainty, quality management, occupational safety and inefficient resource use. This paper presents a narrative review of AI applications in construction practice, based on seven published review and perspective papers and a civil-engineering seminar framework. The reported applications are organised across planning and scheduling, cost estimation, quality inspection, safety monitoring, drawing and document management, Building Information Modelling (BIM), geotechnical engineering, surveying, construction equipment and infrastructure maintenance. Machine learning supports prediction and optimisation, computer vision analyses site images and video, natural language processing handles text-based records, and AI-enabled robotics can automate selected repetitive or hazardous tasks. Linking these tools with BIM, sensors, drones, the Internet of Things and digital twins may make project information more timely and more useful. The literature also reports barriers: inconsistent data, fragmented workflows, high initial investment, limited digital skills, cybersecurity and privacy concerns, and unclear accountability. Because AI outputs depend on data quality and site conditions, they should support rather than replace engineering judgement. The paper concludes that responsible adoption needs well-defined pilot projects, data governance, workforce training, independent validation and measurable project outcomes. As a narrative review of selected publications rather than a systematic review, it offers a structured synthesis, not an exhaustive assessment of the research.**

***Keywords*—Artificial intelligence; construction management; machine learning; computer vision; Building Information Modelling; construction safety; digital twins; civil engineering**

I. Introduction

Construction projects combine many interdependent activities, organisations, materials, machines, and site conditions. Decisions made during design and planning can influence cost, duration, quality, safety, and environmental performance throughout a project. Yet project information is often dispersed across drawings, schedules, reports, inspection records, models, and site communications.

Manual review of these sources can be slow, and problems may only become visible after they have affected progress or cost.

Reviews by Abioye et al. [1] and Chen and Ying [2] describe how artificial intelligence has been investigated as a means of supporting construction decisions and addressing problems that conventional workflows do not always manage efficiently.

Artificial intelligence is an umbrella term for computational methods that perform tasks associated with learning, pattern recognition, language processing, prediction, and decision support. In construction, commonly discussed approaches include machine learning (ML), deep learning, computer vision, natural language processing (NLP), optimisation algorithms, and robotics. Their practical value depends on the task and the quality of the information available. For example, a computer-vision model may flag a visible surface crack in a photograph, while a project-analytics model may estimate the likelihood of a schedule delay from historical progress data. Neither output automatically constitutes a final engineering decision.

Recent reviews examine AI in construction management, emerging opportunities and adoption barriers [3]–[7]. Building on them, this paper offers a practice-oriented synthesis of applications relevant to civil engineering. Its aims are to (i) describe the main AI application areas across the construction lifecycle; (ii) discuss expected benefits and implementation limits; and (iii) identify practical priorities for responsible adoption and future research.

II. Review Approach

This paper follows a narrative literature-review approach. Its sources are a seminar presentation titled “AI Technologies in Construction Practice” and the seven published papers listed in the references [1]–[7], which are reviews and perspective papers on AI in construction, construction project management and related applications. The themes reported in these papers were grouped into application areas, benefits, barriers an d future directions.

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The approach is meant to give civil-engineering practitioners an accessible synthesis. It is not a systematic review: no exhaustive database search, formal screening protocol, duplicate-removal procedure or independent quality appraisal was carried out, and the selected papers should not be taken to represent all relevant research.

III. AI Technologies Relevant To Construction

A. Machine learning and deep learning

Machine-learning methods identify patterns in data and use those patterns to make predictions or classifications. In construction, potential uses include estimating project duration or cost, forecasting equipment maintenance needs, assessing risks, and predicting selected geotechnical or structural responses. Deep-learning methods can be particularly useful when the input is complex, such as images, video, or large collections of sensor readings. Their performance depends on representative training data, suitable model selection, and validation on data that were not used to train the model [1], [2].

B. Computer vision

Computer vision processes images or video to identify objects, patterns, or changes. Construction applications include progress tracking, personal protective equipment monitoring, visible defect identification, site mapping, and comparison of observed work with design information. Image-based systems can help prioritise inspections, but lighting, occlusion, camera position, dust, image resolution, and differences between sites may affect accuracy. A detected anomaly should therefore be checked by a qualified person, especially when structural safety is involved [5].

C. Natural language processing and generative AI

NLP can support the classification, search, and extraction of information from specifications, meeting minutes, inspection reports, contracts, and other text-based records. Generative AI may help draft summaries or answer questions over project documents. These uses require safeguards because generated content may omit qualifications, misinterpret technical language, or produce unsupported statements. Outputs should be checked against the source documents, and confidential project information should only be processed using systems approved for that purpose.

D. Robotics, sensors, and digital twins

AI can be combined with robotics and automated equipment to support repetitive or hazardous operations, while sensors and Internet of Things (IoT) devices provide information about equipment, site conditions, and building performance. A digital twin may connect a digital representation of an asset with data collected during operation. These technologies can support monitoring and maintenance, but reliable deployment requires appropriate sensing, interoperable data, clear operating procedures, and human oversight [3]–[5].

IV. Applications Across Construction Practice

A. Planning and scheduling

Construction schedules contain activity durations, logical dependencies, resource limits, and external constraints. AI-based analytics can examine historical project records and current progress data to identify patterns associated with delay and compare possible schedule scenarios [3], [5]. Optimisation tools may help planners test alternative sequences or resource allocations. These results are most useful when linked to a reliable baseline schedule and updated site records. If progress data are incomplete or activities are recorded inconsistently, predictions can be misleading. The project manager remains responsible for interpreting constraints that are not captured in the data.

B. Cost estimation and cost control

Cost-estimation models can use historical project costs, quantities, material prices, labour information, and project characteristics to produce preliminary estimates or flag unusual cost trends [3], [7]. During execution, an AI-supported dashboard may compare actual expenditure with the budget and highlight items that require review. Such tools can improve consistency and speed, but they cannot remove uncertainty caused by market volatility, design changes, local construction methods, or incomplete quantities. Estimates should state their assumptions, data date, confidence limits where available, and exclusions.

C. Quality control and defect inspection

Quality-related applications include identifying visible cracks, surface defects, dimensional deviations, incomplete work, and differences between planned and observed progress. Image-analysis systems can help organise large volumes of inspection data and direct attention to locations that may need closer examination [1], [5]. For concrete crack assessment, a model might classify an image, locate a crack, or segment the crack region. These tasks are different: locating a visible crack does not by itself establish its depth, cause, structural significance, or required repair. Final assessment should use suitable inspection procedures and engineering criteria.

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D. Construction safety

AI-supported safety systems may analyse camera feeds, equipment telemetry, site layouts, and incident records to identify potential hazards [5], [7]. Examples include detecting unsafe proximity between workers and moving machinery, identifying missing personal protective equipment, or highlighting areas with repeated incidents. Such systems can provide alerts, but false alarms and missed detections are possible. Monitoring should be transparent, proportionate, and consistent with privacy and employment requirements. Safety management must continue to include worker participation, training, site inspections, and established safety procedures.

E. Drawing and document management

Construction projects generate multiple drawing revisions, specifications, requests for information, meeting records, and inspection reports. Optical character recognition can extract text from scanned documents, while NLP can classify records and assist search [5]. AI may help compare revisions or summarise correspondence, reducing time spent locating information. However, document-control rules must remain authoritative: the system should identify the source, revision, date, and status of any information returned. A generated summary should not replace review of the governing drawing or specification.

F. AI and Building Information Modelling

Building Information Modelling (BIM) provides structured information about building components and their relationships. When BIM data are connected with schedule, cost, sensor, and site-progress information, AI can support risk identification, planning alternatives, progress assessment, and maintenance decisions. The value of this integration depends on consistent object naming, reliable model updates, agreed data formats, and clear ownership of information. Poorly maintained models can lead to confident but incorrect recommendations. Research on AI adoption repeatedly identifies data integration and standardisation as important challenges [3], [4].

G. Geotechnical engineering

Geotechnical applications may use borehole records, laboratory test results, groundwater observations, and field measurements to assist soil classification or estimate parameters such as bearing capacity and settlement. Models may also help identify patterns relevant to slope stability or ground-risk assessment. These predictions are sensitive to the quantity, quality, and geographical representativeness of the data.

Soil conditions can change over short distances, and an algorithm trained in one geological setting may not transfer directly to another. AI should complement, not replace, site investigation, laboratory testing, design standards, and geotechnical engineering judgement.

H. Surveying and site monitoring

Images and spatial data from drones, cameras, and surveying instruments can be processed to support site mapping, earthwork measurement, stockpile-volume estimation, and progress comparison. Automated analysis can make repeated monitoring more efficient and provide a record of site conditions over time. Accuracy depends on survey control, calibration, flight and image conditions, processing methods, and validation against appropriate measurements. Operational requirements, airspace restrictions, privacy, and site permissions must also be considered.

I. Equipment, robotics, and asset maintenance

AI-enabled equipment systems can combine sensor readings and maintenance histories to identify patterns that may precede component failure [5], [6]. Predictive maintenance can help maintenance teams plan inspections and reduce unexpected downtime when the model is reliable and the consequences of failure are considered. Robotics may support selected tasks such as material handling or repetitive placement. Practical deployment must account for site variability, equipment safety, worker-machine interaction, maintenance capability, and the cost of integrating automated systems.

J. Infrastructure operation and sustainability

AI may support structural health monitoring by analysing sensor data and inspection images to identify changes that warrant investigation. For buildings, energy-management systems can use occupancy and environmental data to support operational control. At the project level, data analytics may help identify material waste, equipment idling, or inefficient resource use. These applications can contribute to sustainability goals, but benefits should be measured rather than assumed. Evaluation may include energy use, material waste, maintenance response time, service life, and the environmental impact of the digital infrastructure itself [1], [3], [7].

V. Potential Benefits And Limitations

A. Potential benefits

The literature points to several potential benefits [1], [4], [6].

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First, AI can process large or repeated datasets faster than manual review, helping teams identify patterns and exceptions. Second, predictive tools may provide earlier warning of schedule, cost, maintenance, or safety risks. Third, image-based inspection can help prioritise areas requiring human attention. Fourth, integration with BIM and project-management systems may improve coordination by bringing together information that is otherwise separated. Finally, automation can reduce workers' exposure to some repetitive or hazardous tasks. These benefits are context-dependent and should be demonstrated through project-level evaluation rather than presented as guaranteed outcomes.

B. Technical and organisational limitations

A recurring limitation is data quality. Construction data may be incomplete, inconsistent, poorly labelled, or stored in incompatible systems. Models may also perform differently when transferred between project types, regions, materials, or site conditions. Other barriers include initial investment, ongoing maintenance, limited staff expertise, resistance to changes in work practices, and difficulties integrating AI with legacy software. The reviewed literature identifies these factors as important reasons why potential benefits do not automatically lead to widespread implementation [1], [3], [4].

C. Ethics, privacy, cybersecurity, and accountability

AI systems can process sensitive project, worker, client, or infrastructure information. Organisations therefore need to define who can access data, how long data are retained, whether they can be shared with external providers, and how security incidents will be handled. Camera-based monitoring can raise privacy and trust concerns. Bias may arise when training data do not represent the people, locations, or conditions where a system is used. Contractual and professional responsibilities also need to be clear when an AI recommendation contributes to a decision. Human review, documented approvals, audit trails, and a process for challenging erroneous outputs are essential safeguards.

D. Reliability and engineering responsibility

The consequences of an incorrect AI output vary by application. A poor document-search result may cause inconvenience, whereas an undetected structural defect or an incorrect geotechnical prediction can create serious risk. Validation should therefore be proportionate to the consequence of error. For safety-critical applications, the model should be tested on representative independent data, its limitations should be documented, and its outputs should be checked using accepted engineering procedures.

AI should be treated as decision support, with responsibility retained by appropriately qualified professionals.

VI. Practical Framework for Adoption

A staged implementation process can help construction organisations avoid investing in tools before their suitability is established:

1) Define the problem and success criteria. Select a specific task, such as progress documentation or maintenance prioritisation, and establish baseline performance.
2) Assess data readiness. Check completeness, accuracy, format, permissions, representativeness, and compatibility with existing systems.
3) Choose a proportionate solution. Compare available tools against project needs, explainability, cost, integration requirements, and vendor support.
4) Run a controlled pilot. Test the tool on a limited project or workflow and compare its outputs with verified observations or established methods.
5) Keep a human approval step. Identify which decisions can be assisted by AI and which require formal professional review.
6) Train the project team. Provide role-specific training and explain model limitations, data responsibilities, and escalation procedures.
7) Monitor performance over time. Track errors, false alarms, missed detections, time saved, cost, user feedback, and changes in site conditions.
8) Review governance and scale gradually. Expand only when the pilot demonstrates measurable value and security, privacy, and accountability requirements are satisfied.

Potential performance indicators include estimate error, schedule forecast error, time required for inspection, defect-detection precision and recall, number of safety alerts confirmed as valid, equipment downtime, data completeness, and cost per monitored unit. Indicators should be selected to fit the application and reported with their measurement method. A tool should not be described as successful solely because it produces outputs quickly.

VII. Research Gaps And Future Directions

First, more independent field validation is needed. Many proposed applications require evaluation under real site conditions, across multiple projects and environmental settings. Studies should report data characteristics, validation procedures, error rates, and the conditions under which the model fails.

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Second, interoperability remains a priority. Common data structures and consistent information-management practices could improve connections between BIM, schedules, sensors, site imagery, and asset-management platforms.

Third, research should examine adoption in small and medium-sized contractors and in regions where digital infrastructure, training, and investment capacity may be limited. Cost-benefit evaluations should include setup, data preparation, licensing, integration, training, maintenance, and governance rather than only the initial purchase price. Fourth, human factors deserve attention: workers and engineers need to understand what a model can and cannot do, and organisations should assess how AI changes roles, responsibilities, and safety practices.

Fifth, future systems should provide better explanations of predictions and clearer records of the data and model versions used. This is particularly important for decisions involving structural integrity, geotechnical risk, and worker safety. Finally, sustainability claims should be supported by measurable outcomes, including resource consumption, waste reduction, energy use, and whole-life performance. These priorities align with the broader review literature, which highlights data governance, workforce capability, system integration, and responsible implementation as continuing challenges [2]–[4], [6].

VIII. Conclusion

Artificial intelligence offers a growing set of tools for supporting construction planning, estimation, inspection, safety monitoring, document management, BIM integration, geotechnical interpretation, surveying, equipment maintenance, and infrastructure operation. Machine learning can support prediction and optimisation, computer vision can analyse images and videos, NLP can help organise project documents, and AI-enabled automation can assist selected physical tasks. These capabilities may improve the speed and consistency of information processing and help teams identify risks earlier.

However, AI does not remove the uncertainty inherent in construction or replace professional responsibility. Its usefulness depends on reliable data, appropriate validation, integration with existing workflows, staff capability, and clear governance. A practical route forward is to start with well-defined problems, test systems through controlled pilots, evaluate outcomes against measurable baselines, and retain human review for consequential decisions.

Because this paper is a narrative synthesis of selected publications, future work should add a systematic literature search and quantitative evidence from field case studies.

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