Artificial intelligence in construction management: A systematic review of techniques, applications, and data practices

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ABSTRACT

Purpose. This study presents an integrated systematic mapping of artificial intelligence (AI) applications in construction management, clarifying technique-domain pairings, data and validation practices, and deployment readiness across the construction lifecycle, addressing fragmentation in prior reviews.

Design/methodology/approach. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidance for study identification and screening and the structured literature review approach, 148 peer-reviewed articles published between 2007 and 2025 across 14 journals were analyzed through bibliometric and thematic synthesis. An open companion web application (https://cm.electriai.com/) was developed, providing bibliometric visualizations, a searchable paper database, and a retrieval-augmented generation (RAG) AI assistant.

Findings. The review shows that AI research in construction management accelerated after 2022 but remains uneven in its technical and methodological development. Technique-domain mapping revealed lock-in patterns: vision-based deep learning (DL) was concentrated in safety, and traditional machine learning (ML) in cost estimation, while optimization, graph neural networks (GNNs), and generative AI remained underexplored. Data constraints persist: 40.5% of studies used datasets below 500 samples, 65.5% relied on private or unreported data, cross-project validation appeared in 1.4% of papers, and explainable AI (XAI) appeared in 3.4%.

Practical implications. Construction stakeholders require coordinated investment in open benchmark datasets, cross-project validation protocols, XAI integration, and interoperable standards for building information modeling and Internet of Things systems.

Originality/value. This review integrates AI techniques, construction domains, data, and validation practices, supported by an open companion web application for verifying, filtering, and querying the evidence base.

Keywords: Artificial intelligence; Construction management; Systematic literature review; PRISMA; Bibliometric analysis; Deep learning; Explainable AI

Manuscript type: Literature review

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INTRODUCTION

The application of artificial intelligence (AI) to construction management has accelerated rapidly, particularly since 2022, as machine learning (ML), deep learning (DL), computer vision, and large language models (LLMs) have been extended to construction tasks ranging from safety monitoring and cost estimation to design automation and document analysis (Adebayo *et al.*, 2025; Pan and Zhang, 2021). This growth reflects both the maturation of underlying AI techniques and the construction sector's sustained interest in addressing well-documented challenges in productivity, safety, and cost performance (Barbosa *et al.*, 2017; Bureau of Labor Statistics, 2024; Mischke *et al.*, 2024). However, the speed at which new techniques have entered the field has outpaced systematic efforts to characterize how AI is being applied across construction domains, which techniques map to which problems, and what data and validation practices support the reported results.

Several reviews have advanced understanding of specific application areas, including construction safety monitoring (Badhan and Samsami, 2025), cost estimation (Shamim *et al.*, 2025), and building information modeling (BIM) integration with AI (Khan *et al.*, 2024; Zhang *et al.*, 2022). Broader syntheses by Abioye et al. (2021) and Pan and Zhang (2021) provided foundational maps of AI in construction engineering and management, and Zhang and Jiang (2026) established a detailed thematic foundation for equipment, safety, and cost management research over the last five years. Complementary perspectives have been offered on AI implementation risks (Wuni, 2025a), critical success factors (Wuni, 2025b), and visual computing applications (Perera *et al.*, 2025).

Building on these contributions, the present review pursues a complementary line of synthesis along four dimensions. First, it extends the observation window to two decades, placing the recent acceleration documented in prior reviews within the longer technique transition before and after 2022. Second, it broadens the thematic scope to a full mapping of eight technique categories against twelve application domains, connecting the domains examined in depth by earlier syntheses with those that remain sparsely covered. Third, it adds a study-level audit of data and validation practices, recording dataset scale, data accessibility, validation strategy, and explainability adoption, a methodological layer that prior reviews were not designed to capture. Fourth, it makes the coded evidence base openly queryable through a companion web application, allowing readers to verify and re-analyze every reported cross-tabulation. Such mapping supports investment prioritization for industry, regulatory guidance for policymakers (Abioye *et al.*, 2021), and identification of underexplored research directions for the academic community (Akinosho *et al.*, 2020), particularly given the post-2022 diffusion of LLMs and vision transformers into construction research (Kampelopoulos *et al.*, 2025).

This study systematically reviews 148 peer-reviewed articles retrieved from Scopus, published between 2007 and 2025 across 14 journals, following the systematic review protocol of Massaro et al. (2016) and the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) reporting framework (Page *et al.*, 2021). The review is guided by four research questions:

- RQ1: How has AI in construction management research evolved in publication volume, geographic distribution, and journal contribution between 2007 and 2025?
- RQ2: What AI techniques and algorithms are applied across construction domains, and what technique-domain pairings dominate the field?

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- RQ3: What data sources, dataset sizes, and validation strategies characterize the reviewed studies, and what do they reveal about methodological rigor?
- RQ4: What research gaps persist, how are they interconnected, and what directions does the evidence support for future work?

To support transparent verification and re-analysis, the reviewed evidence base is made openly queryable through a companion web application (https://cm.electriai.com/) that provides interactive bibliometric visualizations and a retrieval-augmented question-answering interface grounded in the 148 included articles.

The remainder of the paper is organized as follows. Section 2 describes the systematic review methodology, Section 3 presents bibliometric and thematic results, Section 4 discusses key findings and future research directions, and Section 5 concludes with contributions and practical implications.

RESEARCH METHODOLOGY AND DESIGN

This review follows the structured literature review protocol proposed by Massaro et al. (2016), with the identification, screening, and inclusion stages reported in accordance with the PRISMA 2020 statement (Page *et al.*, 2021), which applies to systematic reviews both with and without meta-analysis. Because the reviewed studies span heterogeneous designs, outcome measures, and application contexts, quantitative pooling of effect sizes is not applicable; the synthesis instead combines bibliometric mapping with thematic content analysis, reported in line with the Synthesis Without Meta-analysis (SWiM) guideline (Campbell *et al.*, 2020). The methodology comprises four sequential phases: identification, screening, eligibility assessment, and inclusion. Table 1 summarizes the filtering steps and the number of articles retained at each stage.

Identification and Screening

The identification phase began with a keyword search conducted on the Scopus database in November 2025. Scopus was selected for its broad coverage of engineering, construction management, and computer science journals and its metadata export capabilities for bibliometric analysis. The search query combined "artificial intelligence" OR "AI" with "construction" applied to titles, abstracts, and keywords, covering the period from 2006 to 2026, returning 29,535 documents.

A series of inclusion and exclusion criteria were then applied to reduce the results to a topically relevant set. Documents were limited to English-language journal articles, and subject areas unrelated to the built environment (e.g., medicine, chemistry, neuroscience, pharmacology) were excluded, reducing the set to 3,844 papers. A source analysis of these articles was conducted to identify journals with the highest concentration of AI in construction management research. Based on disciplinary relevance and publication volume, 14 journals were selected (Table 1), reducing the set to 184 articles. All 14 journals are fully indexed in Scopus across the entire search period, so within this journal set the single-database strategy does not affect retrieval completeness; the boundary of the review lies in the journal selection itself. The restriction to 14 journals and to studies applying AI within building construction management narrows the sample relative to reviews with broader retrieval scopes. This boundary reflects a deliberate trade-off: the full-text extraction of dataset sizes, data sources, validation strategies, and explainability practices reported in the Results section requires manual coding at a depth that constrains feasible sample size while preserving coding consistency. Consistent with the review protocol, the coded evidence base is

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restricted to peer-reviewed journal articles to preserve the transparency and reproducibility of the search and screening procedures; industry reports and other grey literature are therefore not included in the coded sample but are drawn upon in the Introduction and Discussion to motivate and contextualize the findings.

Table 1. PRISMA paper selection process

Filter	Paper Selection Process	Remaining Articles
Keywords	TITLE-ABS-KEY (("artificial intelligence" OR "AI") AND "construction")	29,535
Limit	Period: 2006-2026	26,093
Limit	English	23,962
Exclude	Medicine; Chemical Engineering; Biochemistry, Genetics and Molecular Biology; Chemistry; Neuroscience; Immunology and Microbiology; Pharmacology, Toxicology and Pharmaceutics; Nursing; Dentistry; Veterinary; Agricultural and Biological Science; Physics and Astronomy; Health Professions	10,185
Limit	Articles	3,844
Review	Source analysis of the 3,844 articles to identify journals with the highest concentration of peer-reviewed research at the intersection of construction management and artificial intelligence. 14 journals were selected based on their disciplinary relevance, publication volume in the topic area, and recognition within the construction engineering and applied AI fields.	3,844
Limit	Journals: "Automation in Construction", "Journal of Construction Engineering and Management", "Engineering, Construction and Architectural Management", "Engineering Applications of Artificial Intelligence", "Journal of Information Technology in Construction", "Advanced Engineering Informatics", "International Journal of Construction Management", "Expert Systems with Applications", "Journal of Computing in Civil Engineering", "Artificial Intelligence Review", "Journal of Management in Engineering", "Construction Management and Economics", "Built Environment Project and Asset Management", and "Applied Artificial Intelligence"	184
Exclude	Excluded after relevance screening via Rayyan	148

Eligibility Assessment and Inclusion

To determine whether each of the 184 remaining articles genuinely focused on AI applications within construction management, a two-stage eligibility assessment was conducted using two complementary platforms: the Rayyan systematic review software for the initial relevance screening, and Dedoose qualitative analysis software for full-text verification and structured coding.

In the first stage, the 184 articles were screened independently by two researchers in Rayyan based on their titles and abstracts, drawing on the platform's relevance ranking and keyword highlighting features. Articles that addressed AI only in passing, used "construction" in a non-building context (e.g., mathematical construction), or focused exclusively on manufacturing or infrastructure domains outside building construction were excluded. The two reviewers disagreed on one of the 184 records, corresponding to an observed agreement of 99.5% and a Cohen's kappa of 0.98, indicating a high level of inter-rater agreement (Landis and Koch, 1977). The single disagreement concerned a boundary case between infrastructure engineering and construction management scope; it was resolved through joint discussion of the full text against the inclusion criteria and the article was retained, yielding the final set of 148 articles.

In the second stage, the 148 retained articles were imported into Dedoose for full-text verification against three inclusion criteria: (1) the study presents, applies, or critically evaluates an AI technique within a construction management context; (2) the study is published in a peer-reviewed journal; and (3) the full text is accessible for data extraction. The same Dedoose project was carried forward into the data extraction phase described in the next subsection, in which structured codes were applied to each article. Articles were independently reviewed by the research team with conflict resolution to ensure screening and coding consistency.

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Data Extraction and Analysis

Data extraction was performed using a structured coding template capturing the following variables: research location, construction application domain, AI model or algorithm employed, data type and source, dataset size, methodology, research objective, key results, and future research directions. Each article was read in full and coded manually to ensure consistency.

The analysis proceeded in two stages. First, a bibliometric analysis mapped publication trends, geographic distribution, journal-level contributions, and citation patterns using VOSviewer for keyword co-occurrence and collaboration networks, with additional visualizations generated using Python. The keyword co-occurrence analysis used a minimum occurrence threshold of five, so keywords appearing in fewer than five articles are not represented in the network. Second, a thematic content analysis grouped articles by application domain and AI technique category to identify dominant research pipelines, technique-domain pairings, and methodological patterns. Cross-tabulation of technique categories against application domains enabled identification of both well-established research streams and underexplored combinations. For reporting, the nineteen validation strategies identified during coding were consolidated into five groups: basic internal validation, robustness and interpretability validation, generalization validation, empirical and expert-based validation, and a not applicable category covering review and conceptual studies.

Companion Web Application

To support transparent re-analysis and to complement the static figures and tables presented in this review, an interactive companion web application was developed and deployed at https://cm.electriai.com/. The motivation is threefold. First, this review identifies the absence of open, queryable benchmarks as a recurring limitation of AI in construction research (Akinosho *et al.*, 2020; Soman and Whyte, 2020), and a public companion tool applies the same open-infrastructure principle to the review evidence base. Second, the bibliometric and thematic findings rely on cross-tabulations whose interpretive value increases when readers can filter and drill into specific combinations rather than read aggregated counts only. Third, a natural-language interface grounded in the 148 included articles reduces the effort required to verify specific claims or locate the underlying source, in a manner conceptually similar to recent natural-language AI interfaces developed for construction risk identification (Isah and Kim, 2025) and safety training (Hussain *et al.*, 2024).

The application architecture is presented in Figure 1. The system follows a six-layer design that separates source data, offline preparation, browser-loaded data, processing pipelines, the client application, and the presentation layer. The 148 articles retained after the PRISMA filtering (Page *et al.*, 2021) are transformed offline through two parallel workflows. Manual coding conducted in Rayyan (Ouzzani *et al.*, 2016) and Zotero produces four CSV files containing the bibliometric, technique, and validation matrices reported in the Results section. An automated embedding pipeline based on the Gemini text-embedding-001 model produces a JSON file of 148 paper-level vectors at 768 dimensions. These five files are loaded directly into the browser, where two parallel pipelines operate. The visualisation pipeline ingests the CSV files, applies aggregation logic, and renders interactive charts with hover and click drilldowns that open the full record of any cited article. The retrieval-augmented generation (RAG) pipeline embeds user queries with the same model, retrieves the most similar papers by cosine similarity, augments the prompt with the retrieved context, and generates citation-bearing responses through the Gemini 2.5 Flash model via a Cloudflare Worker proxy.

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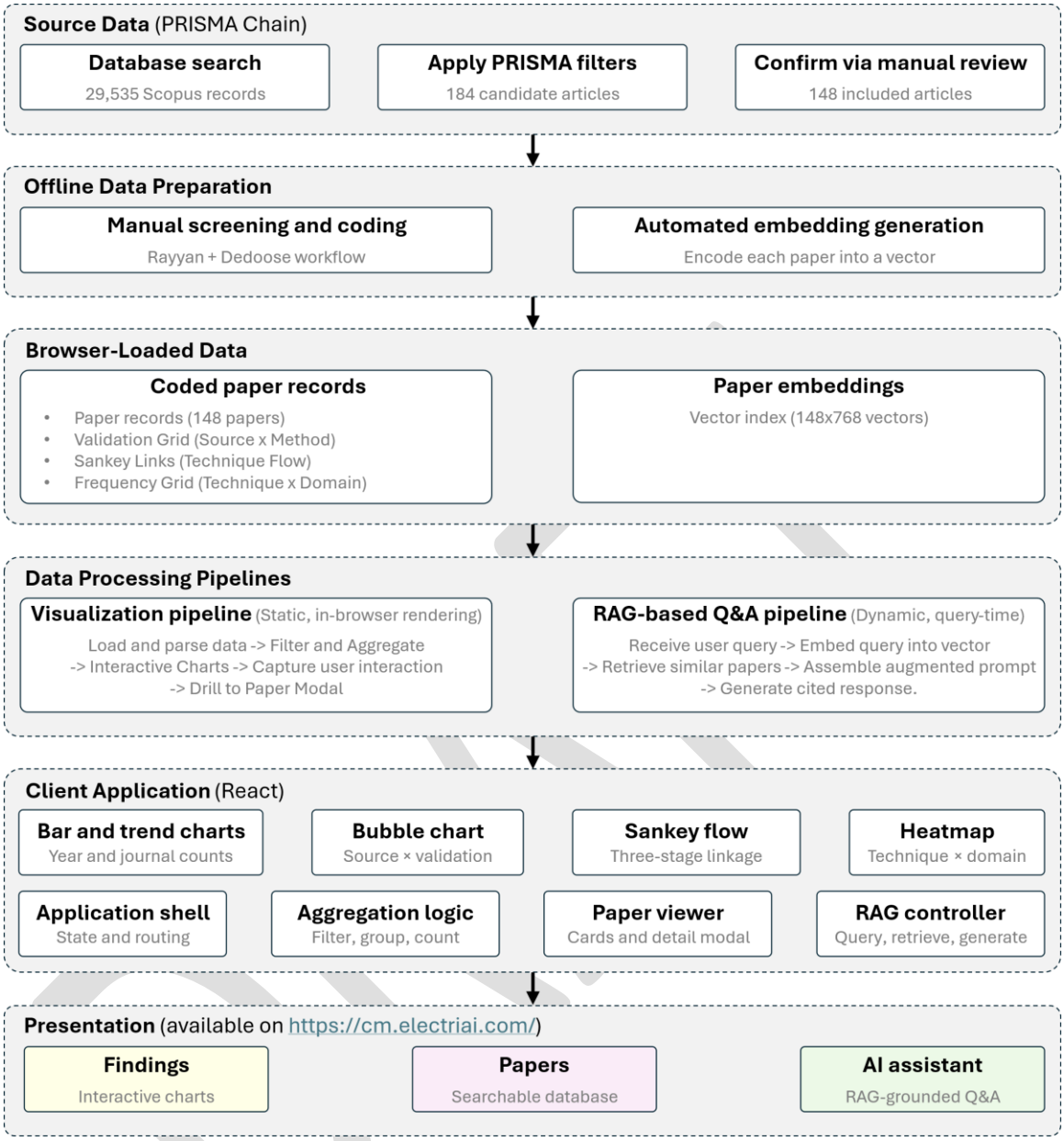


Figure 1. Architecture of the companion web application.

A screenshot of the deployed application is presented in Figure 2. The interface exposes three views: the Findings tab with the interactive charts that correspond to Figures of this review; the Papers tab with a searchable database of all 148 included articles; and the AI assistant tab that returns RAG-grounded answers to natural-language queries. By making the review findings directly queryable, the application supports the open benchmarking, validation transparency, and explainability priorities identified in the Discussion section.

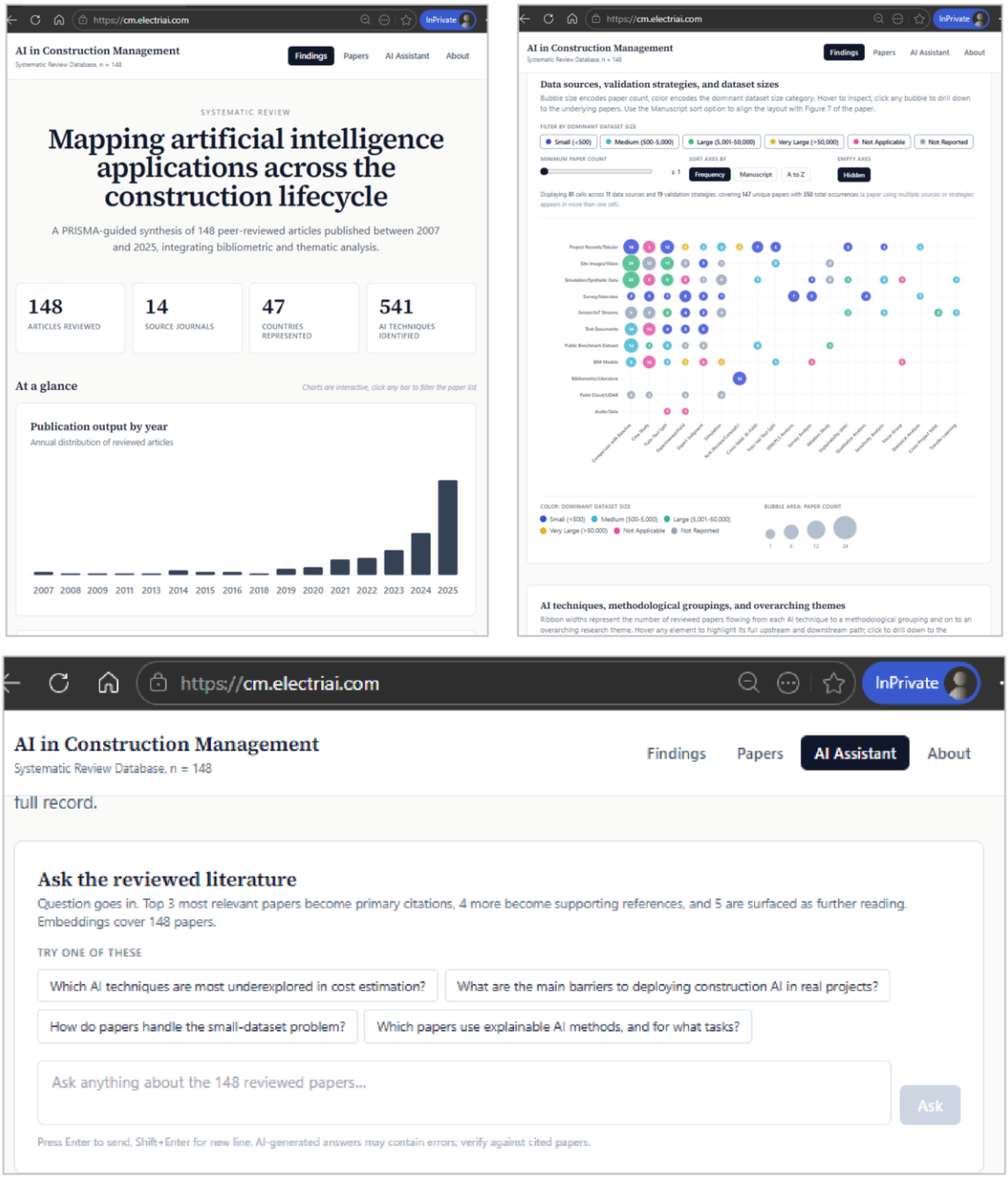


Figure 2. Interface of the companion web application showing the Findings, Papers, and AI assistant tabs.

RESULTS

Publication Trends and Geographic Distribution

Figure 3 presents the distribution of the 148 reviewed articles by publication year and by journal source. Publication output remained minimal from 2007 to 2018 (no more than three papers per year), accelerated from 2019 with the diffusion of DL and computer vision into applied engineering research, and intensified sharply from 2022 onward as LLMs, mature vision-based DL, and

institutional recognition of AI as a strategic priority converged (Naji *et al.*, 2024). The 2024-2025 period alone accounts for 88 papers (59.5% of the reviewed articles). Because the search was conducted in November 2025, the 2025 total of 61 articles covers approximately eleven months of publication activity. On an annualized basis, output rose from 16 articles in 2023 to 27 in 2024 and approximately 66 in 2025. Among the 14 journals surveyed, Automation in Construction dominates with 45 papers (30.4%), followed by the Journal of Construction Engineering and Management (22 papers, 14.9%) and Engineering, Construction and Architectural Management (16 papers, 10.8%), with these three outlets accounting for over 56% of the reviewed articles.



Figure 3. Distribution of reviewed articles by publication year (left) and by journal source (right) (n = 148).

The geographic distribution and collaboration network are presented in Figure 4. China and the United States each contribute 32 papers (43.2% combined), followed by South Korea (25 papers, 16.9%) and the United Kingdom (19 papers, 12.8%). Together, these four countries account for 108 of the 148 reviewed articles, indicating a pronounced concentration of AI in construction management research within a small group of highly active research contexts. Secondary contributors include Australia and Taiwan, China (8 papers each), Hong Kong, China and Canada (7 each). Africa, South America, and most of Southeast Asia remain substantially underrepresented, with no country from these regions contributing more than three papers.

The collaboration network shows China, the United States, the United Kingdom, and Australia at central positions with dense interconnections, while South Korea and Taiwan, China show comparatively fewer international ties despite substantial output. Several of the most methodologically ambitious studies emerged from international partnerships (Badhon *et al.*, 2025; Gao *et al.*, 2025; Liu *et al.*, 2025; Wang *et al.*, 2023), and studies from underrepresented regions illustrate the constraints of resource-limited contexts, including waste prediction trained on only 25 Egyptian sites (Daoud *et al.*, 2025) and cross-border data aggregation across six countries to partially compensate for local data scarcity (Peiman *et al.*, 2025).

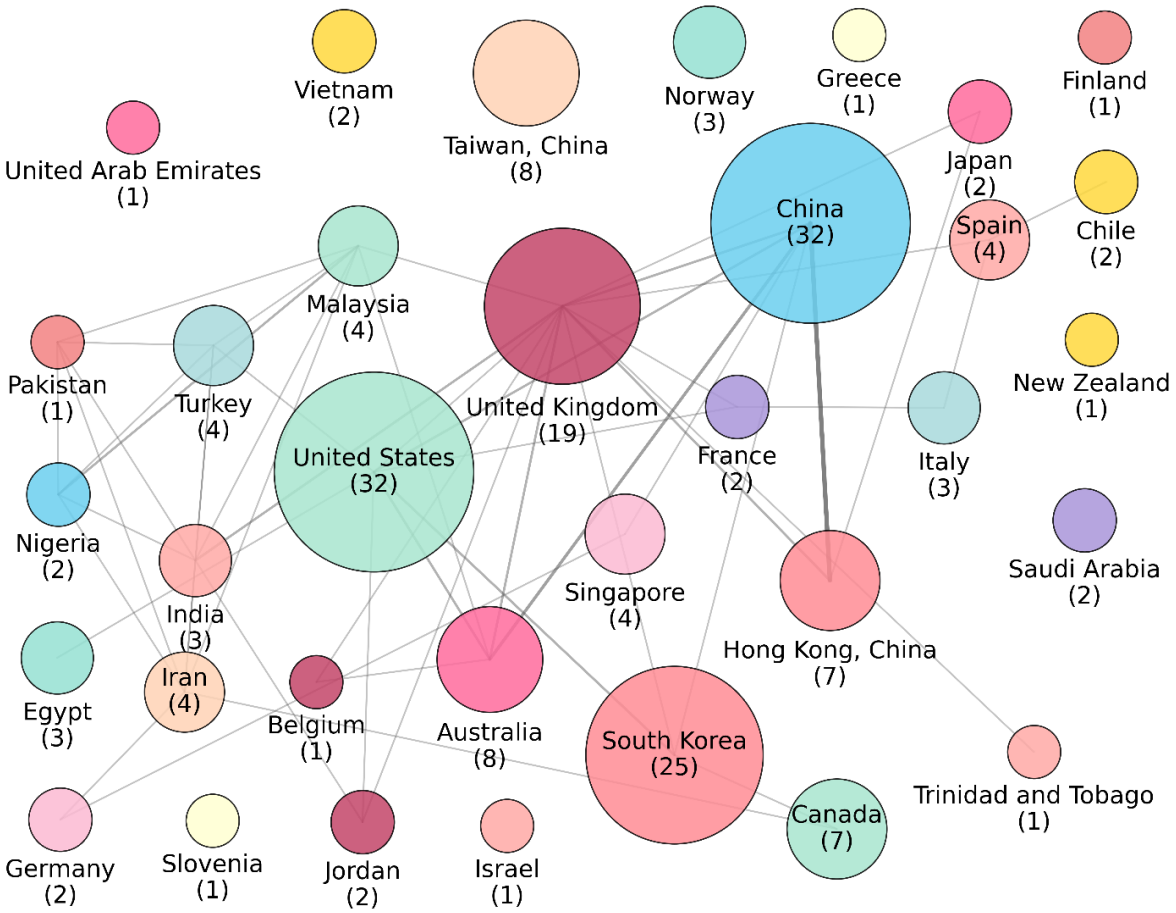


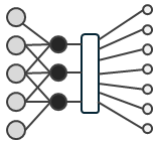
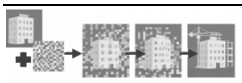
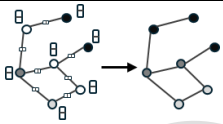
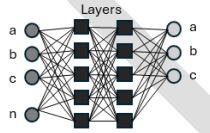
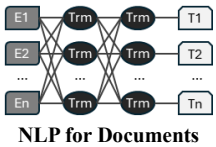
Figure 4. Geographic distribution and international collaboration network of AI in construction research

AI Techniques and Application Domains

Thematic coding of the 148 reviewed articles produced eight AI technique categories, summarized in Table 2. Two structural imbalances are visible within the technique pool itself before any domain mapping is applied. The Deep Learning and Visual Recognition category contains over sixty distinct architectures spanning convolutional neural network (CNN) backbones, two-stage and single-stage detectors, fifteen YOLO variants, vision transformers, segmentation networks, and pose estimation models, whereas Graph-Based BIM contains only six. This asymmetry signals that the field has accumulated dense methodological knowledge in vision tasks and almost none in relational data structures, even though BIM and construction supply chains are inherently graph-structured (Li *et al.*, 2025). The temporal distribution reinforces the point. Before 2022, genetic algorithms (8 papers) and regression methods (7 papers) were the dominant approaches; from 2022 onward, CNN-based papers within the Deep Learning and Visual Recognition category increased from 1 to 19, YOLO detection from 1 to 15, vision transformers from 0 to 13, and LLM and natural language processing (NLP) methods from 5 to 25. The shift carries a reproducibility concern, since 14 of the LLM papers rely on proprietary GPT-4 class APIs whose architectures may be silently updated or deprecated (12 of these papers appeared in 2025 alone), and only a small subset of

studies employed open-source alternatives (Gao *et al.*, 2025; Liu *et al.*, 2025; Naderi and Shojaei, 2025). Random Forest and support vector machine (SVM) baselines continued to appear across both periods, with more modest growth than the newer architectures, suggesting their persistence as benchmark or ensemble components rather than displacement.

Table 2. AI technique categories and the specific models, algorithms, and architectures identified across the 148 reviewed articles.

AI Technique Category	Description	Models, Algorithms, and Architectures Identified
 **Deep Learning and Visual Recognition**	Convolutional and transformer-based architectures applied to image-based detection, classification, segmentation, and pose estimation on construction sites.	• *Backbone CNNs*: AlexNet, VGG-16, VGG-19, ResNet, ResNet-18, ResNet-50, ResNet-101, ResNet-152, DenseNet-161, Inception-ResNet, EfficientNet, EfficientNet-B0, EfficientDet-d0, Xception, CNN, DCNN. • *Two-stage detectors*: Faster R-CNN, Mask R-CNN, Cascade R-CNN, Disp R-CNN. • *Single-stage detectors*: SSD, YOLO, YOLOv3, YOLOv4, YOLOv5, YOLOv5s, YOLOv5m, YOLOv5-x, YOLOv6, YOLOv7, YOLOv7-s, YOLOv8, YOLOv8n, YOLOv10, YOLOX, YOLOX-s, CenterNet. • *Transformer-based vision*: DETR, DDETR, RT-DETR, DINO, DDQ, ViT-base, ViTDet, ViTPose, InternImage-L. • *Segmentation*: U-Net, DeepLabv3+, SAM, SemanticSAM, Mask2Former. • *Pose estimation*: HRNet, AlphaPose, OpenPose, Posenet, SimCC, ST-GCN. • *3D detection*: YoLoStereo3D, SMOKE, FCOS3D, MonoFlex, ImVoxelNet, DSGN, DSGN++, PointNet++. • *Super-resolution*: SRCNN, FSRCNN, ESPCN, mSRCNN. • *Other*: VTransE, Transfer Learning.
 **Generative AI Emergence**	Diffusion models, GANs, and multimodal generative systems for synthetic image generation, layout synthesis, and data augmentation.	• *Diffusion-based*: Stable Diffusion, Stable Diffusion 2.1, SDXL 1.0, ControlNet. • *Text-to-image and 3D scene generation*: DALL-E, DALL-E 2, Midjourney, LayoutGPT, Holodeck. • *Generative adversarial networks*: GAN, CGAN, CoGAN, StyleGAN3.
 **Graph-Based BIM (Graph Neural Networks)**	Graph neural network architectures applied to relational data structures such as BIM models, supply chains, and construction networks.	• *Graph neural networks*: GNN, GCN, GAT, GATv2, GATConv, GraphSAGE. • *Graph pooling operators*: ASAP pooling, SAGPooling.
 **Hybrid Approaches**	Combinations of fuzzy logic with neural networks, evolutionary algorithms, or rule-based systems to encode expert judgment under uncertainty.	• *Fuzzy logic systems*: Fuzzy Logic, Fuzzy set theory, Fuzzy Inference System, Mamdani FIS, Fuzzy-AHP. • *Neuro-fuzzy*: ANFIS, EFNIM, Neuro-fuzzy. • *Belief-based*: Belief Rule-Based.
 **NLP for Documents**	Language models, embeddings, and text analytics methods applied to contracts, specifications, safety reports, and other construction documents.	• *GPT family*: GPT-3.5, GPT-3.5 Turbo, GPT-4, GPT-4 (1106-preview), GPT-4o, GPT-4o mini, ChatGPT, ChatGPT-3.5, ChatGPT-4, ChatGPT 4.5, InstructGPT, o1-mini. • *Anthropic LLMs*: Claude Sonnet 4, Claude 3.5 Sonnet, Claude 3.5 Haiku. • *Google LLMs*: Gemini, Gemini 2.5 Flash. • *Other commercial LLMs*: DeepSeek, DeepSeek-V3, ERNIE Bot, Doubao, Baidu AI. • *Open-source LLMs and frameworks*: Llama2-7B, Llama2-70B, Mistral, Codestral, Ollama, BART, T5, Transformer-XL, Sentence Transformers. • *Multimodal LLMs*: LLaVA, InstructBLIP, CLIP. • *Encoders and embeddings*: BERT, RoBERTa, Word2Vec, GloVe, fastText. • *Topic modeling and classical NLP*: LSA, LDA, spaCy, Stanford CoreNLP, GATE, POS tagging, NER, TextRank, LexRank, KGQA, FSTN. • *Speech*: Whisper.

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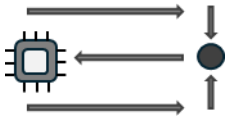
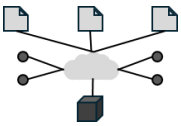
 **Optimization for Design**	Evolutionary algorithms, reinforcement learning, and metaheuristic methods for design optimization, scheduling, resource allocation, and control.	• *Reinforcement learning*: Q-learning, TQL, DQN, DDPG, PPO, TD3, DRL, MDP, Reinforcement Learning. • *Imitation learning*: DIL, GAIL, Behavioral Cloning. • *Evolutionary algorithms*: Genetic Algorithm, NSGA-II. • *Swarm and metaheuristic optimization*: PSO, ICA, ABC, Firefly Algorithm, Simulated Annealing, IGWO, SOS, BDA. • *Control and planning*: MPC, PDDL planners (POPF, LPG).
 **Sensor/IoT Integration**	Recurrent and time-series models applied to sensor streams from wearables, machinery, and site monitoring devices.	• *Recurrent architectures:* LSTM, NN-LSTM, GRU, BiLSTM, BiGRU, SBiGRU, CX-GRU, RNN.
 **Traditional ML for Prediction**	Classical machine learning algorithms including tree-based ensembles, regression, and kernel methods applied to structured tabular data for prediction tasks.	• *Tree-based ensembles*: Random Forest, Extra Trees, XGBoost, LightGBM, CatBoost, AdaBoost, Gradient Boosting, Histogram-based Gradient Boosting, NGBoost, ROSE ensemble. • *Tree-based single learners*: Decision Tree, CART, M5P model tree, Hoeffding Tree, Isolation Forest. • *Kernel methods*: SVM, SVR, SVC, LS-SVC, LSSVM, RVM. • *Linear and regression methods*: Linear Regression, Multiple Regression, Multiple Linear Regression, Multivariate Regression, Nonlinear Regression, Logistic Regression, Symbolic Regression, MARS, EMARS. • *Distance and probabilistic methods*: KNN, Naive Bayes, k-means, GMM, Bayesian Network. • *Basic neural networks*: ANN, BPNN, MLP, DNN, LM-ANN, SCG-ANN, RBP-ANN, RBFNN, ELM, FNN. • *Case-based, rule-based, and association mining*: CBR, FP-Growth, ARM. • *Other*: BAS-BP, LSMBM.

Figure 5 maps the eight technique categories against twelve construction application domains, revealing technique-domain lock-in rather than balanced coverage as the most consequential pattern. DL for visual recognition concentrates in safety and risk management (11 papers) and quality control and inspection (5 papers), with two or fewer papers across each of the remaining ten domains; representative examples include skeleton-based fall detection (Kim *et al.*, 2025), adversarially robust worker safety classification (Anjum and Nnaji, 2025), and pose-based personal protective equipment (PPE) compliance monitoring (López *et al.*, 2025). Traditional ML for prediction clusters in cost estimation and financial management (8 papers), with secondary presence in design automation and specialized engineering analysis (4 papers each) but only 1 paper in geotechnical despite its similar reliance on structured tabular data (Abu-Mahfouz *et al.*, 2025; Chou *et al.*, 2015; Peiman *et al.*, 2025). NLP for documents shows the same shape, with 10 papers in safety and risk and a secondary cluster of 4 in BIM and digital twins, while only 1 to 2 papers reach the remaining domains (Isah and Kim, 2025; Seo and Kang, 2024; Zeberga *et al.*, 2025). These concentrations cannot be explained by data availability alone. Wearable sensors generate exactly the time-series streams that (long short-term memory) LSTM and gated recurrent unit (GRU) architectures are designed to process, yet Sensor/IoT Integration accounts for only 4 papers in total, distributed thinly across safety, cost, project planning, and geotechnical with one paper each, rather than concentrated where the sensing modality fits best (Wang *et al.*, 2023). Optimization techniques cluster in design automation and geotechnical underground construction (4 papers each) and are entirely absent from project planning and scheduling, despite scheduling being a canonical optimization problem (Ghannad and Lee, 2023). The lock-in therefore reflects path-dependent research norms rather than technical fit. Architectural fragmentation within the dominant streams compounds the problem: among the 16 YOLO-based papers, versions range

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from YOLOv3 through YOLOv10 with no convergence toward a standard variant, complicating cross-study performance comparison.

The same heatmap also reveals technique-domain pairings that are notable for their absence. Generative AI appears in only 6 papers, concentrated in safety (3 papers) with single papers across design, project planning, and quality (Davari *et al.*, 2025; Hong *et al.*, 2024; Lee *et al.*, 2025), and synthetic data strategies for tabular, textual, and time-series modalities remain effectively unexplored despite equally severe scarcity in those settings. Graph neural networks (GNNs) and Sensor/IoT Integration are tied as the least represented techniques at 4 papers each, with GNNs absent from safety, geotechnical, quality, BIM, advanced manufacturing, specialized engineering, sustainability, and equipment despite the relational structure of BIM data and construction supply chains (Li *et al.*, 2025). Hybrid fuzzy-neural approaches appear sporadically (8 papers across 6 domains) without concentration anywhere, with a maximum of 2 papers in any single domain, suggesting use as a fallback when domain-specific data are insufficient to support purely data-driven models (Daoud *et al.*, 2025). The collaboration and knowledge management domain exhibits a still different pattern: 14 of its 20 papers (70%) are classified as review or framework studies rather than working AI systems (Jin *et al.*, 2023), indicating that the literature recognizes the importance of AI for organizational coordination but rarely implements computational tools to support it.

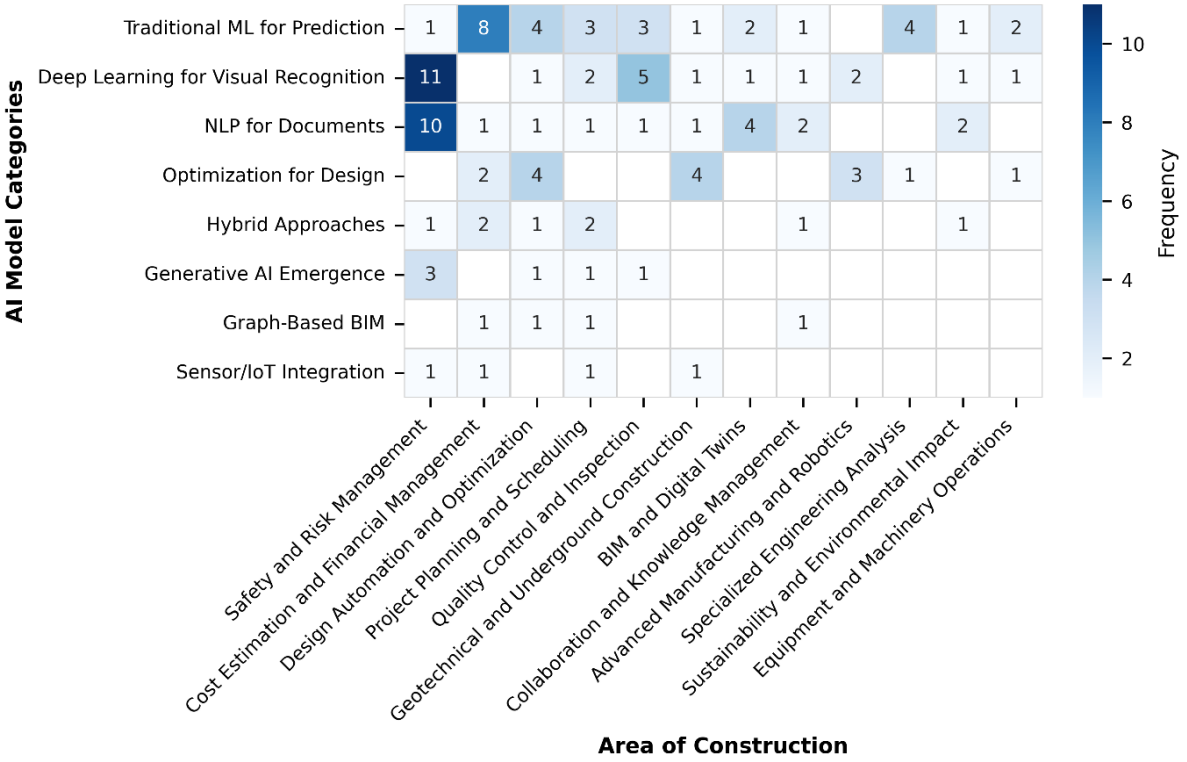


Figure 5. Distribution of AI technique categories across construction application domains.

Figure 6 traces the same 148 papers through five methodological groupings into six overarching research themes. Two further imbalances emerge from Figure 6. First, the Perception & Vision AI grouping (30 papers) distributes across multiple research themes, with 6 to 7 papers each flowing into Performance & Efficiency, Data & Knowledge Infrastructure,

Safety/Sustainability/Compliance, and Integration & Scalability, yet only 1 paper flows into Trust & Transparency. The vision-DL stream therefore pursues efficiency, integration, and safety goals without proportionate attention to interpretability, even though safety-critical deployment is what motivated these methods entering the field (Akinosho *et al.*, 2020). Second, the Research Methods & Validation grouping, which captures meta-level and review studies, contributes 42% of papers reaching Data & Knowledge Infrastructure (8 of 19) and 33% of papers reaching Trust & Transparency (5 of 15). The themes most urgently requiring computational implementation are therefore the same themes most often discussed without one, a misalignment consistent with the high proportion of "No Specific AI Model" papers identified.

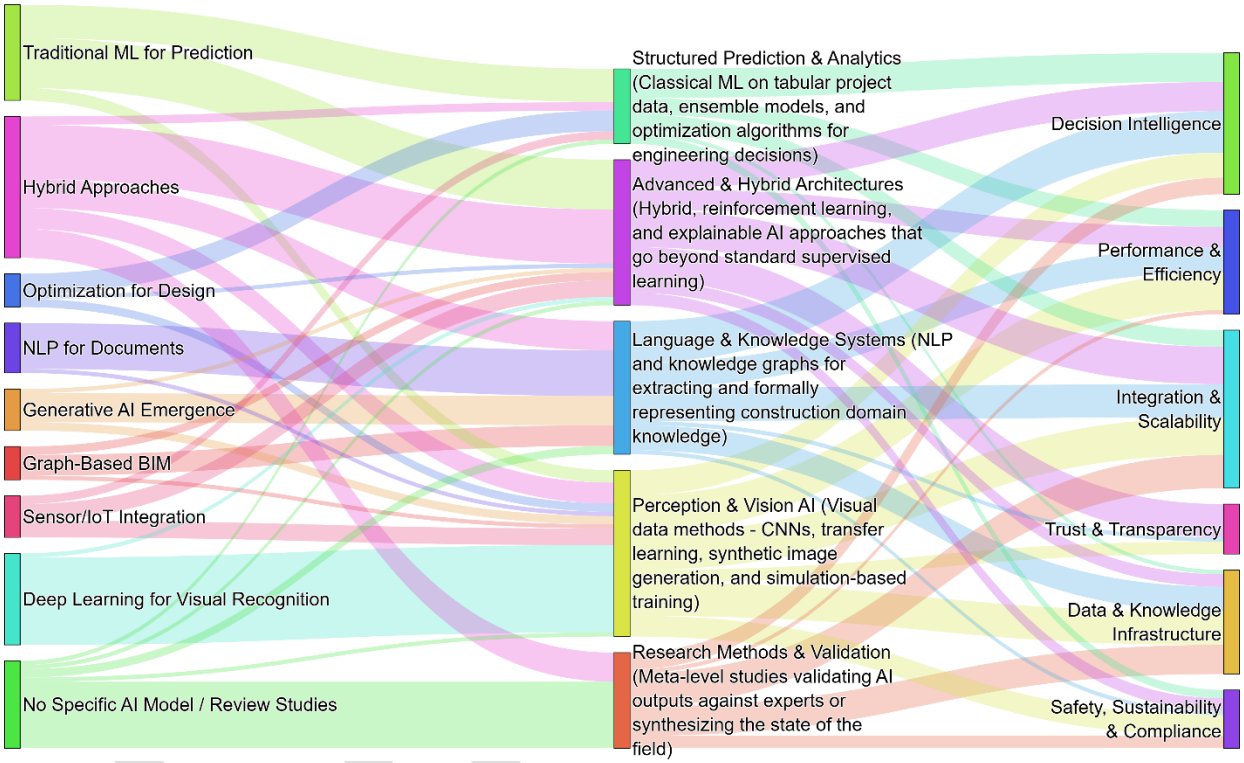


Figure 6. Sankey diagram of AI technique-methodology-theme linkages in construction research.

The keyword co-occurrence network in Figure 7 corroborates these patterns and surfaces two additional structural features. Keywords related to LLMs and NLP occupy peripheral positions with smaller node sizes and fewer links to the dominant clusters, indicating that LLM-based research, despite its rapid publication growth, remains loosely tied to the established core of AI-construction scholarship rather than integrated within it. Conversely, terms related to explainability, fairness, ethical AI, and data governance do not appear as visible nodes anywhere in the network, confirming that the field remains oriented toward predictive accuracy at the expense of the sociotechnical conditions required for responsible deployment in safety-critical environments (Badhon *et al.*, 2025).

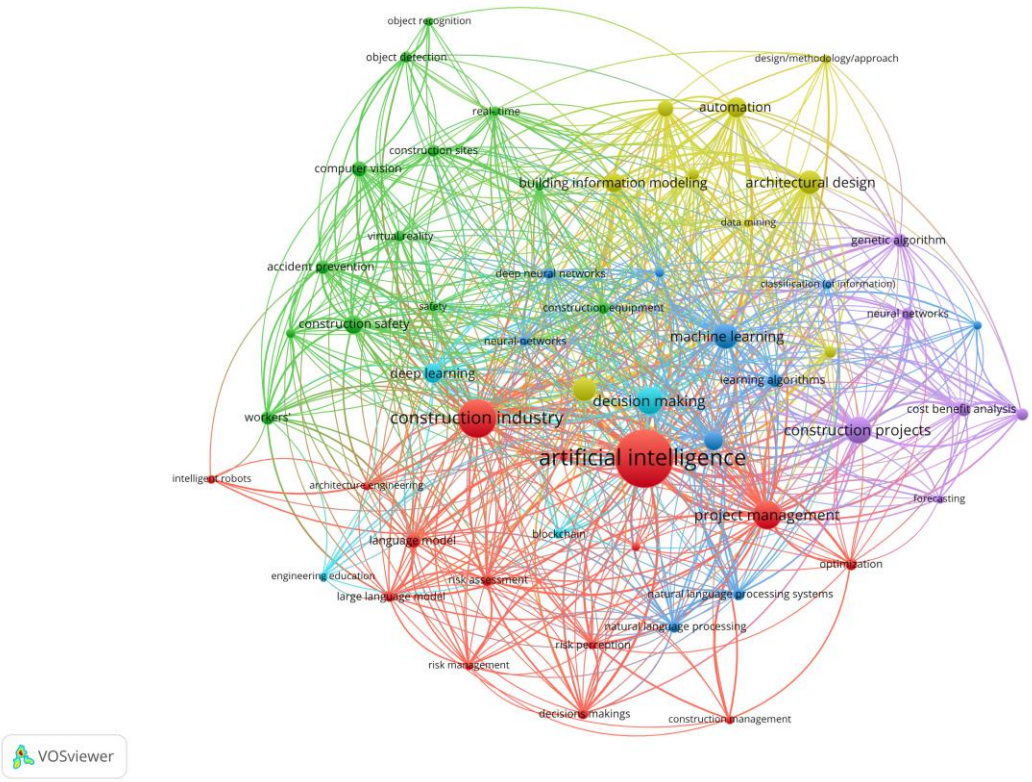


Figure 7. Keyword co-occurrence network of AI applications in construction research

Data Characteristics and Validation Practices

Figure 8(a) maps eleven data source types against nineteen validation strategies organized into five groups across the 148 reviewed articles, with bubble size indicating paper count and color representing dominant dataset size. Figure 8(b) summarizes the frequency of each strategy by group. Three systemic weaknesses emerge: persistent reliance on small, proprietary datasets; a validation culture skewed toward low-rigor protocols; and narrow exploitation of available sensing modalities.

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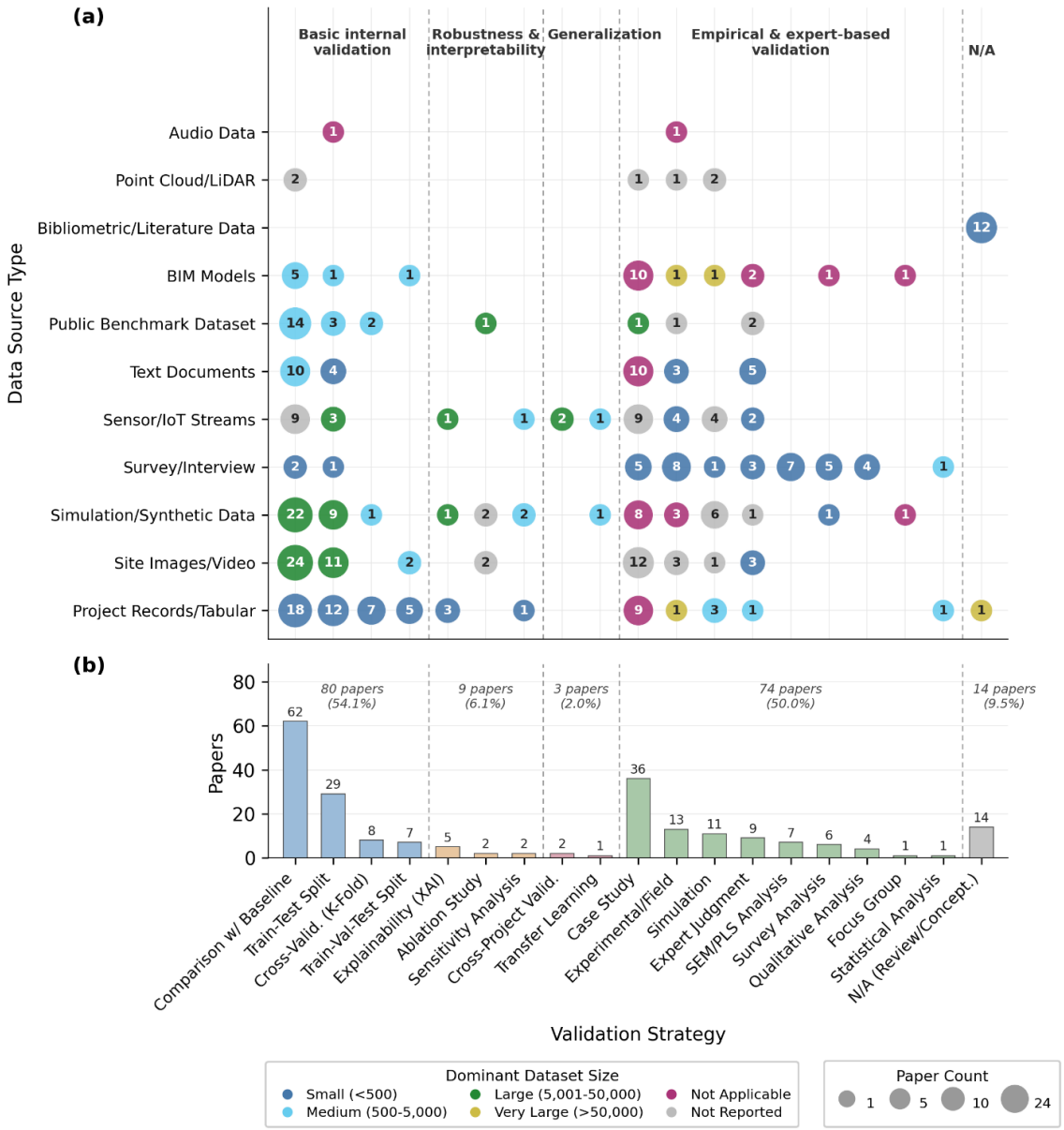


Figure 8. Data source types and validation practices across the reviewed AI in construction literature (n = 148): (a) data source types mapped against nineteen validation strategies organized into five groups; (b) frequency of individual validation strategies with group subtotals.

Four data sources dominate: project records and tabular data (40 papers, 27.0%), site images and video (35 papers, 23.6%), simulation and synthetic data (33 papers, 22.3%), and survey or interview data (29 papers, 19.6%), with text documents and sensor/IoT streams in a middle tier at 23 and 21 papers respectively. Several data types remain severely underrepresented despite growing availability on modern construction sites: point cloud and LiDAR appear in only 4 papers (Trzeciak and Brilakis, 2023), audio in one (Elelu *et al.*, 2023), and multi-modal inputs combining language-based AI with site-level sensing in one (Liu *et al.*, 2025). This concentration on visual

and tabular data indicates that the field has not systematically exploited the full sensing range available for construction site digitization.

The most significant finding concerns dataset scale. Of the 148 papers, 60 (40.5%) operate on small datasets of fewer than 500 samples while only 10 (6.8%) employ datasets exceeding 50,000 instances, and a further 35 papers (23.6%) either do not report dataset size or classify it as not applicable, creating a transparency gap that inhibits assessment of model reliability. The small-dataset problem is most acute in studies relying on proprietary organizational records that are difficult to aggregate across firms and projects (Abu-Mahfouz *et al.*, 2025; Chou *et al.*, 2015; Peiman *et al.*, 2025). A growing subset of 21 papers employs synthetic data generation to compensate for labeled data scarcity (Davari *et al.*, 2025; Hong *et al.*, 2024; Lee *et al.*, 2025; Zhao *et al.*, 2025), though this strategy remains concentrated in vision-based safety and quality tasks despite equally severe scarcity in tabular, textual, and time-series contexts.

The reproducibility constraint compounds the scale problem. Approximately 65.5% of the reviewed papers rely on private data (69 papers, 46.6%) or data whose availability is not stated (28 papers, 18.9%); only 33 papers (22.3%) use publicly accessible datasets and 17 (11.5%) combine public and private sources, and one theoretical or conceptual paper is classified as not applicable. The majority of reported results therefore cannot be independently verified or benchmarked, a condition at odds with the standards of a maturing field (Akinosho *et al.*, 2020).

Validation practices show parallel concerns. Comparison with baseline models is the most common strategy (62 papers, 41.9%), followed by case study evaluation (36 papers, 24.3%) and train-test split (29 papers, 19.6%). However, 90 of 148 papers (60.8%) employ only a single validation component without triangulation or robustness checks, and among the 60 small-dataset papers, 51 (85%) do not employ k-fold cross-validation or a train-validation-test split. Validation strategies assessing real-world transferability are almost entirely absent: cross-project validation appears in only 2 papers (1.4%), both in the geotechnical subdomain (Wang *et al.*, 2023; Zhang *et al.*, 2025). Given the heterogeneity of construction projects in scope, site conditions, and regulatory environments, a model validated solely on its source project provides limited evidence of utility elsewhere. At the group level, 54.1% of the reviewed articles employ at least one basic internal validation strategy and 50.0% employ empirical or expert-based validation, whereas robustness and interpretability strategies appear in 6.1% of the papers and generalization strategies in only 2.0%.

Explainability constitutes the final critical gap. Only 5 papers (3.4%) employ explainable AI (XAI) methods such as SHAP or LIME, and ablation studies appear in just 2 (1.4%). Existing contributions span dedicated XAI frameworks for project risk assessment (Badhon *et al.*, 2025), LIME-based vulnerability analysis under adversarial conditions (Anjum and Nnaji, 2025), causal reasoning embedded in GRU architectures (Wang *et al.*, 2023), and SHAP-based materials prediction (Vairagade *et al.*, 2025). Despite these contributions, the field remains oriented toward predictive accuracy rather than the transparency required for safety-critical deployment, where the inability to explain predictions represents a significant barrier to practitioner trust and regulatory acceptance.

DISCUSSION AND FUTURE RESEARCH DIRECTIONS

Table 3 consolidates the 14 gap themes identified through thematic coding into six research gap clusters, reporting for each cluster the number of contributing papers, technique and domain distributions, data practices, and the most frequently recommended future research directions.

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435
436 **Table 3. Research gap clusters, evidence synthesis, and future research directions derived**
437 **from the 148 articles.**

Research Gap Cluster	Technique, Domain, and Data Characteristics	Recommended Future Directions and Supporting Evidence
C1. Data Infrastructure Deficiencies (n = 71, 48.0%) *Limited data availability; domain-specific data scarcity; data quality concerns*	**Techniques**: Traditional ML (22.5%), CNN/DL Visual (21.1%), NLP/LLM (18.3%), GAN/Generative (7.0%) **Domains**: Safety and Risk (23.9%), Design and BIM (14.1%), Cost Estimation (12.7%), Collaboration and Organizational (9.9%), Geotechnical (9.9%) **Data**: Project Records/Tabular is the leading data source (25.4%), followed by Simulation/Synthetic (19.7%); 43.7% of papers use small datasets (<500)	• Develop open, domain-specific benchmark datasets for underserved areas such as sustainability and geotechnical engineering (Daoud et al., 2025; Wang et al., 2025). • Extend synthetic data generation beyond images to tabular and time-series modalities (Elghaish et al., 2026; F. Liu et al., 2024a). • Establish cross-organizational data sharing protocols to aggregate project records across firms and regions using structured data standards and decentralized governance (Adel *et al.*, 2022; Soman and Whyte, 2020).
C2. Automation of Manual and Labor-intensive Processes (n = 54, 36.5%) *Manual process reliance; insufficient automation*	**Techniques**: CNN/DL Visual and NLP/LLM (each 24.1%), RL/Optimization and Traditional ML (each 14.8%) **Domains**: Safety and Risk (24.1%), Design and BIM (20.4%), Scheduling and Planning (9.3%), Quality and Inspection (9.3%) **Data**: Images/Video leads (22.2%), followed by Text/Documents (18.5%), Simulation/Synthetic and Project Records/Tabular (each 16.7%); 22.2% use small datasets (<500)	• Build end-to-end pipelines linking detection outputs to workflow management and decision-support systems (López *et al.*, 2025; Malekaee Ashtiyani et al., 2026). • Expand NLP-based risk identification to multilingual and multimodal contexts, including conversational AI interfaces and knowledge graph-based retrieval systems (Hussain *et al.*, 2024; Isah and Kim, 2025). • Integrate BIM, IoT, and digital twin platforms to create automated, ML-driven feedback loops for real-time resource monitoring (Elghaish et al., 2026; Sadeghi et al., 2026).
C3. Real-world Deployment Readiness (n = 80, 54.1%) *Limited real-world validation; insufficient real-time capability*	**Techniques**: CNN/DL Visual (25.0%), NLP/LLM and No Specific Model (16.2%), Traditional ML (12.5%) **Domains**: Safety and Risk (28.7%), Equipment and Robotics (11.2%), Design and BIM (10.0%), Geotechnical (8.8%) **Data**: Images/Video and Simulation/Synthetic co-lead (each 23.8%); 30.0% use small datasets (<500); larger datasets and real-world validation are the most cited future concerns	• Prioritize validation protocols that test model robustness across diverse construction scenarios, including varied occlusion conditions and synthetic-to-real domain gaps (Davari *et al.*, 2025; Kim *et al.*, 2025). • Develop lightweight, edge-deployable architectures for real-time inference on resource-constrained site hardware (Kim and Xiong, 2025) • Conduct comparative field trials benchmarking AI monitoring systems against current manual and sensor-based practices using operational metrics such as detection accuracy, deployment cost, and response time (Moohialdin *et al.*, 2023)
C4. Methodological and Technique Limitations (n = 59, 39.9%) *Technique gaps; limited generalizability*	**Techniques**: Traditional ML (27.1%), CNN/DL Visual (20.3%), NLP/LLM (16.9%), RL/Optimization (11.9%) **Domains**: Safety and Risk (23.7%), Cost Estimation (18.6%), Design and BIM and Geotechnical (each 11.9%), Equipment and Robotics, Scheduling and Planning, and Specialized Engineering (each 6.8%) **Data**: Project Records/Tabular leads (33.9%); 35.6% of papers use small datasets (<500)	• Prioritize physics-informed hybrid approaches and transfer learning to improve prediction under limited data conditions (Liu et al., 2024b). • Mandate out-of-sample, cross-project, and cross-regional validation as standard practice to improve model transferability (Peiman *et al.*, 2025). • Invest in workforce AI literacy and training programs to reduce adoption barriers and build construction professionals' confidence in AI-assisted decision-making (Emaminejad *et al.*, 2024; Jang *et al.*, 2021).
C5. System Integration and Holistic Frameworks (n = 73, 49.3%) *Fragmented system integration; absence of holistic frameworks*	**Techniques**: No Specific Model (27.4%), NLP/LLM (19.2%), Traditional ML and CNN/DL Visual (each 13.7%), RL/Optimization (12.3%) **Domains**: Design and BIM (26.0%), Collaboration and Organizational (15.1%), Safety and Risk (13.7%), Scheduling and Planning (9.6%) **Data**: Simulation/Synthetic leads narrowly (16.4%), followed by Images/Video, Survey/Interview, and Bibliometric/Literature (each 15.1%); 28.8% use small datasets (<500)	• Develop interoperable AI-BIM-IoT-digital twin architectures with standardized data exchange protocols (Gao *et al.*, 2025; Zheng *et al.*, 2024). • Transition from conceptual frameworks to empirical validation through pilot deployments on active construction projects (You *et al.*, 2024; Zeberga *et al.*, 2025). • Establish industry-wide data and workflow standards that reduce fragmentation and enable cross-platform AI deployment (Jin *et al.*, 2023; Pishdad-Bozorgi and Onungwa, 2024).
C6. Interpretability, Trust, and Responsible Adoption (n = 43, 29.1%) *Limited interpretability; adoption barriers; security and robustness concerns*	**Techniques**: No Specific Model (41.9%), NLP/LLM and Traditional ML (each 14.0%), CNN/DL Visual and RL/Optimization (each 9.3%) **Domains**: Collaboration and Organizational (25.6%), Safety and Risk (16.3%), Equipment and Robotics (14.0%), Design and BIM and Geotechnical (each 11.6%), Cost Estimation (9.3%)	• Develop and validate explainable AI frameworks tailored to construction decision-making, enabling practitioners to audit model outputs (Badhon *et al.*, 2025; Naumets and Lu, 2021). • Design longitudinal studies tracking how AI adoption and trust evolve across stakeholder roles and project types (Emaminejad et al., 2024; Liu & Liu, 2026)

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	Data: Survey/Interview dominates (37.2%); 46.5% use small datasets (<500)	• Establish industry-specific standards for AI transparency, data governance, and security in safety-critical applications (Kochovski and Stankovski, 2021; Zheng *et al.*, 2024).

The proportion of papers that do not implement a specific AI model serves as a useful indicator of research maturity within each cluster. Cluster C6 (Interpretability, Trust, and Responsible Adoption) has the highest proportion at 41.9%, followed by C5 at 27.4%. By contrast, C2 (Automation of Manual and Labor-intensive Processes) records only 6.0%. This disparity reveals a bifurcation in the literature: while automation-focused research has progressed to the stage of building, testing, and benchmarking computational systems, the equally critical agendas of trust, interpretability, and system integration remain anchored in survey-based and framework-oriented scholarship. If this imbalance persists, the field risks developing technically sophisticated AI tools that construction stakeholders neither understand nor trust, and that cannot be integrated into the fragmented information ecosystems that characterize real construction projects.

The geographic concentration identified in the results compounds these methodological concerns. Over 72% of the reviewed articles originate from four countries (China, the United States, South Korea, and the United Kingdom), and AI solutions validated in the data-rich, highly digitized environments of these economies may not transfer effectively to contexts where digital maturity is lower, construction processes are more labor-intensive, and training datasets are scarce (Wuni, 2025a). The collaboration network further reveals that most cross-national partnerships connect geographically proximate or economically linked countries, with fewer collaborations bridging the divide between high-income and low-income economies. Addressing this disparity will require deliberate investment in research partnerships that connect established methodological hubs with the contextual knowledge of underrepresented regions, alongside the development of open, shareable datasets enabling model validation across diverse construction contexts.

The patterns identified in the reviewed literature can be assessed against recent industry evidence. RICS (2025) surveyed more than 2,200 built environment professionals and reported that 45% had no AI implementation in their organizations and fewer than 1% reported fully embedded organization-wide use, with the leading barriers to adoption being lack of skilled personnel (46%), integration with existing systems (37%), and data quality and availability (30%). In a survey of 235 United States general and trade contractors, Dodge Construction Network (2025) found that 87% of respondents expected AI to have a meaningful impact on construction, yet only 19% were actively adapting workflows for an AI environment and only 26% rated their current data quality as high, while the ability to understand how an AI solution reaches its conclusions was the factor most frequently selected as influencing future adoption decisions (68%). Autodesk (2025) similarly reported that the share of leaders across design and make industries who expected AI to enhance their industry declined from 78% to 69% between its 2024 and 2025 survey editions, with trust in AI technologies falling by 11 percentage points, indicating that early expectations are being tempered by implementation experience. These practitioner-reported conditions converge with the gap clusters derived from the 148 reviewed articles: data quality constraints correspond to cluster C1, skills shortages to cluster C4, system integration barriers to cluster C5, and the gap between expectations and operational deployment to cluster C3, while the demand for transparent AI decision-making parallels cluster C6, where explainability methods appear in only 3.4% of the reviewed studies (Autodesk, 2025; Dodge Construction Network, 2025; RICS, 2025). Industry recommendations prioritizing open data standards, workforce upskilling, and the embedding of explainability, fairness, and transparency into AI tools (RICS, 2025) align with the future research directions in Table 3. This convergence indicates that

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the constraints identified in this review reflect observable conditions of current practice rather than artifacts of the journal sample.

CONCLUSION

This study systematically reviewed 148 peer-reviewed articles on AI applications in construction management, spanning 2007 to 2025 across 14 leading journals. The analysis yielded four principal contributions. First, the bibliometric mapping revealed that the field is in a phase of rapid expansion, with 59.5% of the reviewed articles published in 2024 and 2025, but concentrated geographically in four countries that together account for over 72% of the sample. Second, the technique-domain mapping identified significant lock-in patterns, with vision-based DL confined predominantly to safety applications and traditional ML clustered in cost estimation, while optimization, sensor integration, GNNs, and generative AI remain underexplored across most construction domains. Third, the data and validation analysis exposed critical limitations: 40.5% of studies use datasets under 500 samples, 65.5% rely on private or unreported data, cross-project validation appears in only 1.4% of papers, and XAI methods in only 3.4%. Fourth, the gap cluster analysis demonstrated that the field's unresolved challenges form an interconnected web rather than isolated problems, requiring coordinated investment in data infrastructure, validation standards, explainability integration, and system interoperability.

For construction industry stakeholders, these findings highlight the need for investment not only in AI model development but also in data infrastructure, workforce training, interoperability standards, and explainability requirements that collectively determine whether research prototypes translate into operational value on construction sites. This review is subject to several limitations. The restriction to 14 journals may exclude relevant work published in other venues, including the engineering and computer science outlets indexed in IEEE Xplore and Web of Science. Similarly, the restriction to peer-reviewed articles excludes industry reports and other grey literature, which are used in this review for contextualization rather than as coded evidence; future reviews could incorporate grey literature through structured quality appraisal procedures. The search query, while broad, may not capture all AI-related terminology used across subfields. The coding of application domains and technique categories involved interpretive judgment, and while systematic procedures were followed, alternative classification schemes could yield different groupings. Future reviews could also expand the journal set, incorporate multiple databases, and apply automated text mining to complement manual coding.

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