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Transforming Construction Risk Management and Resource Optimization: A Machine Learning and Big Data Perspective

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Abstract

This integrative literature review examines the role of machine learning (ML) and big data analytics in transforming risk management and resource optimization in construction projects. Following a PRISMA-P-guided search across Scopus, Google Scholar, Web of Science, and PubMed, 5,756 initial records were identified and screened, resulting in a final dataset of 154 eligible studies, of which 59 high- and moderate-quality studies were retained for detailed synthesis after quality assessment. The review highlights ML's enhanced predictive capabilities for risk assessment and resource allocation, supported by cross-industry comparisons and construction-specific case studies. Representative findings from the literature include reported prediction accuracies of up to 93.75% for delay-risk prediction and 97.6% for equipment matching, indicating the potential of ML-based tools to improve forecasting, monitoring, and resource-allocation decisions. The review also highlights the synergistic integration of ML with Building Information Modeling (BIM), the Internet of Things (IoT), and digital twin technologies, which collectively enhance project efficiency despite challenges in data-sharing standardization, interoperability, and regulatory compliance. Key barriers to ML and big data adoption are identified, along with strategic measures to address them. The study proposes two novel frameworks for the construction sector: an AI-Enhanced Construction Risk Prediction and Mitigation Framework and a Smart Build: AI-Optimized Resource Management Framework. These frameworks, informed by insights from industry practitioners, policymakers, and researchers, aim to advance digital transformation in construction by providing structured approaches for leveraging ML in risk management and resource optimization.

Keywords

Machine learning; big data; construction projects; resource optimization; risk management

INTRODUCTION

A. CASE STUDY

Machine Learning (ML) has become a transformative tool in construction project management, enhancing efficiency, reducing waste, and improving safety across the project lifecycle [1]. Advancements in big data analytics, affordable computing, and sophisticated algorithms have accelerated ML adoption, particularly in areas like building performance and energy modelling [2]. Subfields such as computer vision, robotics, and reinforcement learning further expand ML's potential to boost safety, productivity, and sustainability [3].

Despite these advancements, risk management and resource optimization remain major challenges due to the inherent complexity, uncertainties, and dynamic interdependencies of construction projects. Common issues include contract-related risks, cognitive biases, and limited automation, which hinder knowledge transfer and timely decision-making [4], [5]. Resource optimization is complicated by conflicting objectives and unpredictable constraints [6].

A 2024 Deloitte report notes that over 40% of construction firms now use big data and ML to improve risk forecasting and resource planning, achieving a 25% improvement in cost accuracy [7]. Similarly, a 2023 study found an 18% reduction in equipment idle time via AI-driven predictive allocation [8]. However, only 30% of firms have the digital infrastructure needed to scale these tools effectively.

While AI and ML offer significant potential, most existing studies are retrospective, with limited theoretical or empirical contributions. To address this gap, this study introduces conceptual enhancements integrating ML with traditional risk and resource management. Key innovations include:

1. Automation of risk prediction using supervised and unsupervised ML models.
2. Hybrid approaches combining ML with heuristic optimization for resource planning.

This research addresses the following questions:

1. How effective are ML-based and hybrid approaches in managing risks and optimizing resources in construction?
2. What lessons can be drawn from ML applications in other sectors to benefit construction?
3. How do adoption rates and influencing factors vary geographically?
4. What are the key barriers to ML and big data adoption in construction?
5. How can integrated frameworks enhance the implementation of ML for risk and resource management?
6. What are the current research gaps and future opportunities?

B. OBJECTIVE OF THE PAPER

The objectives of this study are threefold: first, to evaluate the impact of data-driven methodologies, particularly ML and big data analytics, on enhancing risk management and resource allocation in construction projects; second, to identify, categorize, and analyze the significant barriers to adopting these technologies, including their root causes and effects on project outcomes; and third, to develop actionable frameworks for implementing ML and big data techniques to optimize these critical metrics.

This study pioneers an integrative approach [9] to ML and big data analytics in construction project management, synthesizing empirical evidence to compare ML-based and hybrid methods with traditional approaches, analyze global adoption trends, and identify key barriers. Unlike prior reviews that address technology or risk management in isolation, this study employs the PRISMA-P framework for methodological rigor and introduces actionable frameworks—AI-Enhanced Risk Prediction and Smart Build Resource Management—to bridge research and practice. It further distinguishes itself by incorporating cross-industry benchmarking and technology convergence insights, offering a multidimensional perspective rarely explored in existing literature. With stakeholder-informed recommendations and a focus on practical implementation, this study serves as a foundational guide for advancing AI-driven transformation in construction.

METHODOLOGY

A. LITERATURE REVIEW APPROACH

This research adopts an integrative literature review approach to examine the adoption of ML and big data for risk management and resource optimization in construction projects, as per Figure 1. Unlike systematic reviews [10] or hybrid bibliometric analyses [11], this method enables a comprehensive synthesis of theoretical and empirical studies, drawing from peer-reviewed journals, conference proceedings, technical reports, and industry case studies. By analyzing ML algorithms, big data analytics, and their integration with construction technologies such as BIM and IoT, this review not only identifies advancements and challenges but also contextualizes findings within construction management, uncovering interdisciplinary opportunities.

Distinguished from bibliometric analyses that aggregate data without offering practical insights[11], [12], this review emphasizes actionable solutions for stakeholders, including risk and procurement managers. It systematically evaluates global adoption trends, barriers, and implementation challenges, ensuring a structured yet forward-looking analysis. Moreover, it contributes to theoretical development by synthesizing existing research to propose novel perspectives [13], aligning with the argument that a well-designed integrative review leads to a deeper understanding of the research landscape and future directions [14]. To our knowledge, this is the first large-scale study dedicated to exploring ML and big data applications in construction specifically for resource optimization and risk mitigation, offering both academic and practical contributions.

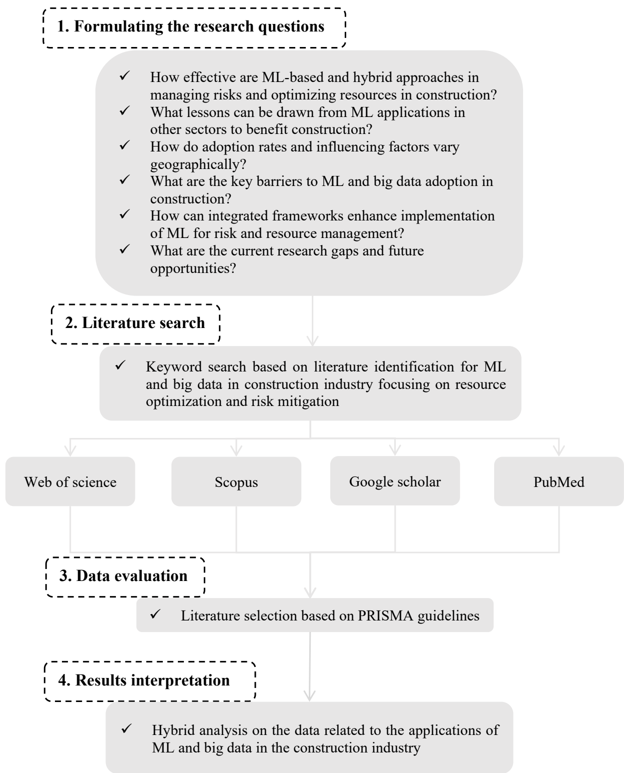

Figure 1 Research methodology

This study has two main objectives, first is to evaluate the performance of the existing building structure with a conventional fixed base system. The second is retrofitting the existing buildings with the addition of a base isolation system and evaluating its performance. Gravity loads such as dead load due to self-weight (DL), additional dead load (SIDL), live load (LL) are applied to the slab and beam elements. The evaluated method uses nonlinear time-history analysis as required in Tier 3 analysis of ASCE 41-17. The observed parameters to be compared are the dynamic characteristics (natural period and modal mass participation factor), base shear, roof acceleration, roof drift ratio, interstory drift ratio, the number of plastic hinge formed, hinge condition, energy dissipation ratio.

B. SEARCH OF THE LITERATURE

The literature search was conducted using Scopus, Google Scholar, Web of Science (WoS), and PubMed, selected for their broad interdisciplinary coverage, robust indexing standards, and high citation tracking capabilities. Scopus and WoS provide extensive peer-reviewed literature across engineering, data science, and management, while Google Scholar ensures the inclusion of grey literature and conference papers. Although PubMed primarily focuses on health sciences, it offers valuable insights into construction-related safety and occupational risk management. Specialized databases like Springer and IEEE were excluded due to redundancy, as their indexed content is largely covered within Scopus and WoS.

A comprehensive keyword strategy was employed to optimize retrieval effectiveness, incorporating primary terms such as "machine learning," "big data," "deep learning," "reinforcement learning," and "AI decision-making." Supplementary keywords included "neural networks," "data mining," "computer vision," "genetic algorithms," "transfer learning," and "Bayesian networks," along with domain-specific terms like "risk management," "resource optimization," "safety management," and "construction hazards." Boolean operators and phrase searching were used for Scopus and WoS, while Google Scholar allowed broader searches, and PubMed queries focused on safety and risk-related topics in construction. Additionally, a reverse keyword search was conducted by reviewing key papers' reference lists to refine search terms further.

C. INCLUSION AND EXCLUSION CRITERIA

To ensure methodological rigor and alignment with the study's objectives, the following inclusion and exclusion criteria were applied during the literature screening phase by the PRISMA-P framework:

Table 1 Inclusion and Exclusion Criteria for the Integrative Review on Machine Learning and Big Data in Construction Risk Management and Resource Optimization

Criterion Type	Inclusion Criteria	Exclusion Criteria
Thematic Relevance	Studies applying ML, AI, or big data to construction risk management or resource optimization	Studies applying ML or big data in non-construction sectors without transferable insights
Technological Integration	Includes use od BIM, IoT digital twins, or UAVs in conjuction with ML/big data	Focuses on general automation or digitization without risk/resource focus
Publication Type	Peer-reviewed journal articles, conference papers, technical reports, and case studies	Editorials, blog spots, white papers, or non-peer-reviewed content
Time Frame	Published between 2020 and 2024	Published before 2020 or outside the targeted window
Language	Written in Engllish	Written in other languages without available translations
Access and Availability	Full-text accessible through Scopus, WoS, PubMed, and procedures	Abstract-only, paywalled without institutional access, or not indexed in main databases
Methodological Transparency	Provides clear description of models, datasets, and procedures	Lacks empirical validation or methodological work
Redundancy	Unique contributions not duplicated in other publications	Duplicates or summaries of previously included work

D. DATA ASSESMENT

Data Assesment

The screening process followed the PRISMA-P framework. [15] as per Figure 2, ensuring rigor and transparency. The initial search yielded 5,756 references, which were systematically filtered through four phases: (1) Duplicate removal excluded 982 references; (2) Title screening eliminated 4,277 references outside construction projects; (3) Abstract screening removed 266 references unrelated to AI-driven approaches; and (4) Full-text screening excluded 84 studies that did not align with the focus on resource optimization and risk management. The final dataset comprised 154 publications, ensuring a focused and high-quality literature base.

Quality Assessment

To ensure methodological rigor, a structured quality assessment followed the initial screening. This step evaluated the reliability, validity, and contribution of each study selected for review.

A tailored appraisal checklist was created using established tools (e.g., Mixed Methods Appraisal Tool, Critical Appraisal Skills Program) to suit various study types (empirical, technical, case-based). The checklist included seven criteria:

1. Clarity of objectives
2. Suitability of design and methods
3. Transparency of data sources
4. Reproducibility of analysis
5. Validity of results
6. Credibility of source
7. Practical or theoretical contribution to construction risk or resource management

Each criterion was rated Yes, Partially, or No. Studies were classified as:

1. High quality : ≥5 "Yes"
2. Moderate : 3–4 "Yes"
3. Low : <3 "Yes"

Of 237 full-text articles assessed post-PRISMA-P filtering, 154 met the inclusion criteria and were appraised. Only High and Moderate quality studies were retained for synthesis, totalling 59 cited papers. Low-quality studies, though excluded, informed gaps and reporting issues in the field.

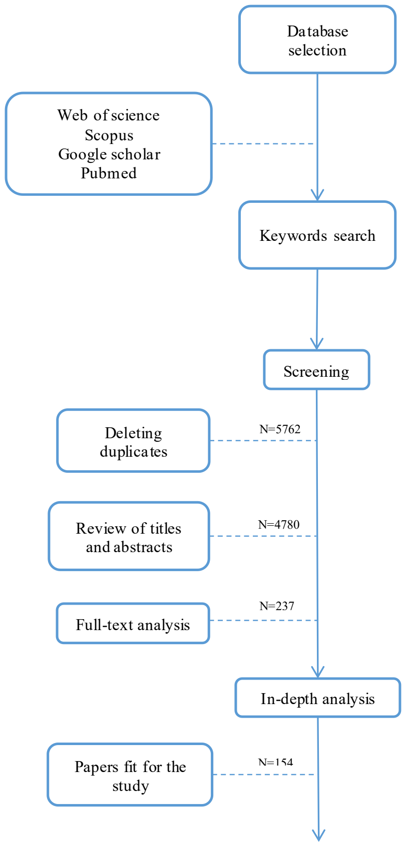

Figure 2 PRISMA-P framework

Readiness Level Assessment

Beyond quality, the review assessed the maturity of ML and big data applications for deployment in construction. A readiness scale, inspired by Technology Readiness Levels (TRLs), classified studies into:

1. Low: Conceptual/lab stage (TRL 1–3)
2. Medium: Pilot or simulated environment (TRL 4–6)
3. High: Field deployment with results (TRL 7–9)

The 154 eligible studies were rated accordingly, based on implementation context, data, and validation level. Among the 59 cited, most demonstrated medium to high readiness, highlighting both practical potential and a persistent gap between research and application.

E. LITERATURE ANALYSIS

Publication Sources

The present analysis focuses on publications related to ML and big data in the construction industry, as retrieved from Scopus, PubMed, Web of Science, and Google Scholar databases. This analysis covers peer-reviewed journal papers, conference papers, technical reports, case studies, and comparison papers. The data shows that research in this field is published across various journals, with Automation in Construction leading significantly with approximately 33 publications. Other journals, such as the Journal of Construction Engineering and Management and the International Journal of Construction Management, also feature a notable number of publications, though far fewer than Automation in Construction, as per Figure 3. This distribution highlights the broad academic interest in leveraging ML and big data technologies to address challenges in the construction industry while emphasizing the dominant role played by certain specialized journals.

Year Of Publication

This analysis includes papers published between 2020 and 2024 to ensure that the review reflects recent advancements, trends, and challenges in ML and big data applications in construction. As shown in Figure 4, the annual distribution of publications indicates a clear decline from 2020 to 2023, followed by a modest recovery in 2024. Specifically, the dataset included 50 studies in 2020, 44 studies in 2021, 29 studies in 2022, 14 studies in 2023, and 17 studies in 2024. This trend suggests that the initial surge of ML and big data studies in construction during 2020–2021 was followed by a consolidation period, with renewed interest emerging in 2024, particularly around integrated AI, BIM, IoT, and digital twin applications.

Keywords

A co-occurrence analysis of authors' keywords from the reviewed articles was conducted using VOS viewer to identify dominant research themes as per Figure 5. The most frequently occurring keywords—"machine learning," "artificial intelligence," and "construction industry"—underscore the increasing role of AI-driven technologies in construction. Key research clusters include "deep learning," "computer vision," and "construction safety," highlighting their relevance in monitoring and risk assessment. Strong connections with "BIM," "risk management," and "IoT" emphasize the integration of data-driven decision-making in construction workflows.
Additionally, specialized applications such as "predictive analytics," "reinforcement learning," "neural networks," and "digital twins" reflect the diverse methodologies

employed. Emerging themes like "construction scheduling," "safety culture," "productivity monitoring," and "automated borders" indicate the growing sophistication of AI applications. The analysis reveals that ML and big data are evolving beyond standalone tools to integrated systems addressing complex challenges in safety, scheduling, and resource optimization. The rise of advanced techniques such as reinforcement learning, generative adversarial networks (GANs), and digital twins signals a shift from descriptive analytics toward predictive and prescriptive solutions, marking a new frontier in AI adoption in construction.

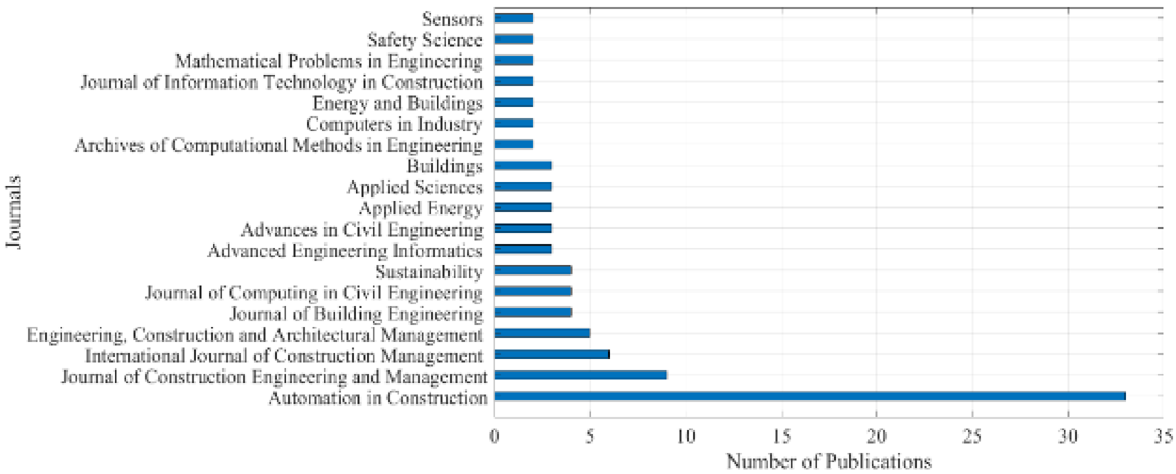

Figure 3 Publishing sources analysis

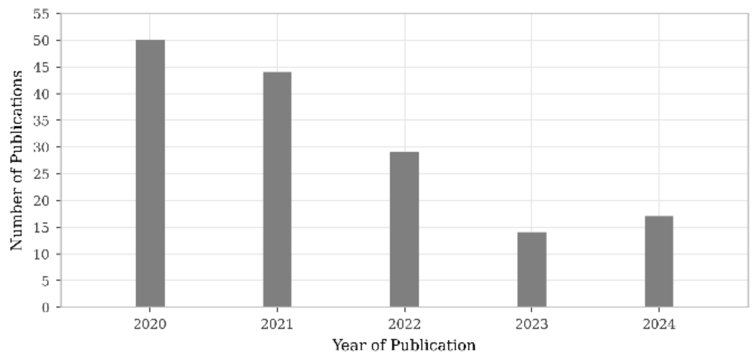

Figure 4 Year of publication analysis

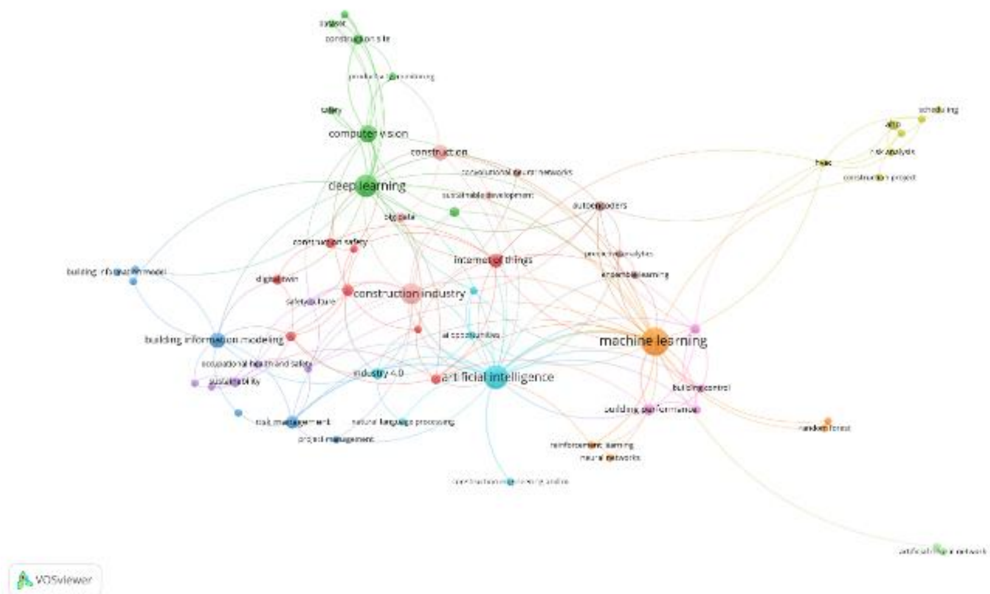

Figure 5 Mapping of Keywords Co-occurrence

F. KEY CONTRIBUTIONS OF THE STUDY

This review contributes to the AI and construction project management literature through a rigorous, practice-oriented analysis. Key contributions include:

1. Integrated Perspective on Risk and Resource Optimization: Unlike prior studies addressing these separately, this review jointly examines how ML and big data tackle both risk and resource inefficiencies.
2. Dual Evaluation Methodology: A two-stage appraisal—(i) quality assessment and (ii) readiness level analysis—ensures both methodological rigor and practical relevance.
3. Empirically Grounded Frameworks: Two actionable frameworks are developed:
   a. AI-Enhanced Construction Risk Mitigation
   b. Smart Build: AI-Driven Resource Management

These draw on high-readiness studies and address common barriers like data silos and cost limits.

1. Cross-Sectoral Insights and Transferability: By benchmarking against sectors like healthcare and manufacturing, the study identifies transferrable practices and hybrid modeling strategies.
2. Practical Roadmap for AI Adoption: A four-phase roadmap supports industry-scale deployment, incorporating benchmarks, training tools, and policy guidance.
3. Research Gaps and Future Directions: The review highlights key gaps—e.g., explainable AI for safety, multimodal sensing, and ethics frameworks—guiding future research priorities.

THE ROLE OF ML AND BIG DATA IN CONSTRUCTION PROJECTS

A. FOUNDATIONAL CONCEPTS

Traditional construction risk management and resource optimization have relied on reactive methods and manual data interpretation, which are ill-suited for today's complex, fast-paced projects[16], [17]. These methods fail to address the dynamic interdependencies of modern construction, where early risk detection and real-time decision-making are critical.

The emergence of predictive machine learning (ML) has shifted this paradigm by leveraging historical and real-time data to anticipate hazards. In safety monitoring, ML models proactively identify high-risk scenarios and help prevent incidents[18], [19]. Concurrently, prescriptive analytics, driven by big data and ML, enable real-time decision-making, notably in modular construction, where activity recognition enhances factory efficiency[16], [20]. This transition from reactive to predictive and prescriptive approaches (see Figure 6) transforms static data into foresight, enhancing responsiveness and resource allocation[21], [22], [23]. However, adoption remains limited. Many ML applications are still experimental, hindered by data silos, lack of standardization, and poor model interpretability.

Moreover, while several studies highlight ML's potential, few assess its scalability, robustness, or cost-effectiveness across diverse projects and organizations. Addressing these gaps requires implementation frameworks that integrate technical innovation with organizational readiness and process transformation.

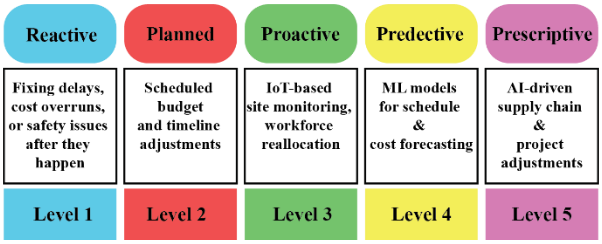

Figure 6 Transition from reactive to predictive and prescriptive approaches

B. APPLICATION OF ML AND BIG DATA IN CONSTRUCTION

Resources Optimization

Literature consistently supports using ML and big data to enhance resource efficiency in construction. These tools enable real-time monitoring and dynamic reallocation of materials, labor, and equipment. For example, multi-camera vision systems have achieved 97.6% accuracy in equipment matching, significantly reducing productivity errors ([n.d.-a]). Similarly, digital twins and Smart MiC Objects improve material tracking and waste reduction[24], [25].

Despite these advances, most studies focus on specific applications. The integration of ML with BIM and VR for aligning planned and actual conditions[26] shows potential for proactive planning, but generalizability across diverse projects remains limited. Models like ANNs and SVMs improve labor and material allocation[27],XGBoost demonstrates predictive strength for resource inefficiencies[28], yet few assess their long-term performance or compatibility with legacy systems.

ML is also applied to delay risk prediction, with some models achieving up to 93.75% classification accuracy[29]. However, most focus on technical accuracy rather than integration into organizational workflows or feedback loops. While ensemble methods and visualization tools promote foresight and collaboration[26], [30], their impact on team behavior and project management remains underexplored. Overall, although ML tools show increasing technical maturity, further empirical work is needed on their systemic integration into construction operations[31].

Risk Prediction and Mitigation

The predictive capabilities of ML in construction risk management are well-documented. Random forests have proven effective in identifying risk-prone workers and forecasting fatal incidents using demographic and organizational data[18]. Similarly, integrating fuzzy Bayesian networks with fault tree analysis supports dynamic risk assessment, particularly in complex geotechnical projects such as metro station construction [28].

Despite methodological advances, practical implementation remains limited. Studies on green construction cost prediction via XGBoost[32] demonstrate high algorithmic accuracy but often neglect adaptability to evolving project conditions. Digital twin-enabled systems in modular construction represent a move toward real-time risk mitigation[33], yet fragmented data and inconsistent model validation hinder broader adoption.

Moreover, while ML models report strong metrics, their application in real-time decision-making and contractor guidance is underexplored. There is a pressing need to assess ML's impact on safety protocols, negotiation processes, and stakeholder accountability. Future research should evaluate how these tools shape behavior, mitigate latent hazards, and promote ethical risk governance in routine construction practice.

Illustrative Case Studies

ML and big data have provided transformative solutions in the construction industry, particularly in the domains of risk management and resource optimization. The following case studies in Table 2 illustrate successful implementations, summarizing their results, key findings, and practical implications.

Table 2 Case studies of ML applications in construction projects

Problem	AI approach used	Performance	Challenges faced	Lessons learned
Labor injury risk (Subedi and Pradhananga 2021)	Sensor-based supervised prediction	95% accuracy; RMSE = 9.05 Nm for back moment	High data cost; sensor calibration	Calibrated data improves accuracy
Predicting labor injury risk (Choi and others 2020)	Random forest (logistic regression)	AUC = 91.98% for high-risk workers	Imbalanced data; feature selection	Ensembles address imbalance
Collapse risk in foundation pits (Zhang and others 2020b)	Fuzzy Bayesian network + Fuzzy AHP	Effective decision support for risk prevention	Uncertainty modeling; subjective inputs	Fuzzy logic handles uncertainty well
Fast Personal Protective Equipment Detection for Real Construction Sites (Zijian Wang and others 2021)	YOLO v5x model	86.55% mAP; YOLO v5s fastest; 7% drop on blurred faces	Image blur; poor quality	Quality data boosts detection
Highway Construction Safety Analysis (Smetana and others 2024)	Large Language Models	Identified top accident types & patterns	Unstructured data; LLM adaptation	Prompt tuning enhances LLM output

Table 3 evaluates the performance of various ML models in the construction industry based on three criteria: adaptability, scalability, and accuracy. Adaptability assesses the model's ability to handle diverse data types and dynamic environments; scalability measures its capacity to manage growing data volumes and project complexity; and accuracy reflects the precision and reliability of its outputs. These criteria were assessed through literature and case study reviews, focusing on demonstrated effectiveness in construction applications such as risk management, resource optimization, and predictive analytics. The frameworks column offers step-by-step guidance for implementing each model in real-world scenarios, ensuring relevance to industry needs. These frameworks outline processes such as data collection, training, and deployment, tailored to address challenges like risk prediction, resource allocation, and safety monitoring. This structured evaluation helps stakeholders select and deploy ML models that best meet construction challenges while offering actionable pathways for integration.

Table 3 Performance Evaluation of ML Models in Construction: Adaptability, Scalability, Accuracy, and Application Frameworks

Model	Adaptability	Scalability	Accuracy	Application framework
Sensor-Based Computational Approach	High	Medium	High	IoT → Data preprocessing → ML for maintenance & optimization
Random Forest Method	High	High	High	Historical data → Risk prediction → Resource optimization
Fuzzy Bayesian Network	Medium	Medium	High	Identify risks → Assess via FBN → Mitigate
Fuzzy Analytical Hierarchy Process	Medium	Low	Medium	Set criteria → Prioritize → Plan
You Only Look Once Model	High	High	High	Real-time detection → Safety monitoring & tracking

Model	Adaptability	Scalability	Accuracy	Application framework
Large Language Models	Medium	High	Medium	Train on docs → Automate reports & compliance
Graph Neural Networks	High	Medium	High	Graph modeling → Optimize logistics/resources
Long Short-Term Memory Networks	High	Medium	High	Forecast timeline/cost → Link to tools
GANs	Medium	Medium	Medium	Generate data → Simulate risk/planning
Extreme Gradient Boosting	High	High	High	Train on data → Predict cost/risk
Deep Q-Learning	Medium	Low	Medium	Autonomous scheduling/optimization
Support Vector Machines	Medium	Medium	High	Classify for defects & safety
Recurrent Neural Networks	High	Medium	High	Sequence analysis → Predict delays
Autoencoders	Medium	Medium	Medium	Anomaly detection → Track deviations
Transformers	High	High	High	NLP for contracts & communication
Reinforcement Learning	Medium	Low	Medium	Workflow & equipment optimization via agents
Capsule Networks	Medium	Low	Medium	Structural image recognition
Hierarchical Clustering	Medium	Medium	Medium	Grouping for resource planning
Diffusion Models	Medium	Medium	Medium	Outcome simulation under uncertainty
Elastic Net Regression	Medium	Medium	High	Feature selection + regression for cost/risk

CURRENT STATE OF ADOPTION IN THE CONSTRUCTION PROJECTS INDUSTRY

A. TECHNOLOGICAL ECOSYSTEM

Tools And Software Commonly Used

The growing array of ML and big data tools in construction highlights increasing potential, yet the ecosystem remains fragmented and underutilized. Algorithms like random forests, SVMs, deep neural networks, and ensemble models are widely applied to tasks such as accident prediction, material demand, and delay estimation[34], often without systematic model selection or benchmarking. Scalable platforms like Hadoop and Spark support real-time analytics[17], but their integration with construction-specific tools and their handling of noisy, fragmented data are rarely assessed empirically. Advanced ML applications—including YOLO for object detection and XGBoost for feature-rich regression—signal a shift toward domain-adaptable modeling[34], [35], yet issues like training time, maintenance, and resource constraints in field settings are largely overlooked.

In risk analytics, hybrid models combining Bayesian networks and decision trees have achieved high accuracy, up to 93% in safety threat detection[18], [36]—but remain poorly integrated into decentralized, subcontractor-driven workflows. Despite growing model diversity, gaps persist around interoperability, feedback loops, and long-term maintainability. Future research should pivot toward deployment frameworks that address stakeholder roles, retraining protocols, and scalability across diverse organizational contexts.

Integration with Existing Construction Technologies

The synergy between ML, big data, and both legacy and emerging construction technologies is widely recognized as central to digital transformation. Integration with BIM enables predictive insights, such as safety alerts or scheduling risks, within 3D environments[37], [38], streamlining workflows and improving site visibility. Yet, issues with data exchange standards and semantic alignment remain key barriers.

IoT sensors provide granular data on equipment, environment, and worker behavior, and their combination with ML has proven effective for predictive maintenance and labor tracking[19]. However, adoption is hindered by high costs, surveillance concerns, and data security issues. UAVs equipped with computer vision accelerate monitoring in low-visibility or spatially complex sites[39], [40], though limitations persist regarding flight regulations, weather, and alignment with ground-based BIM data. Similarly, ML-enhanced AR/VR tools show potential in safety training and planning[41], but their long-term effectiveness in learning retention and task performance under real conditions remains underexplored.

As summarized in Table 3, while these technologies offer clear benefits, recurring integration, scalability, and standardization challenges persist. Future research should shift from technical feasibility to system-wide interoperability, user adoption strategies, and impact metrics capturing productivity gains and cultural transformation in construction.

Table 4 Emerging ML techniques in Construction: Applications, Benefits, Challenges, and Future Opportunities

Technology	ML Applications	Key Benefits	Challenges	Future Opportunities
Building Information Modeling	• Clash detection • Progress tracking • Generative design	• Cuts design errors & rework • Boosts risk detection by 30% • Improves cost accuracy	• Poor data interoperability • Limited AI use due to no standards	• Generative AI for sustainable design • Real-time design validation
IoT Sensors	• Predictive maintenance • Resource & labor tracking • Safety & fatigue detection	• 30% less downtime • Better real-time decisions • Improved safety compliance	• High IoT deployment cost • Privacy concerns over surveillance	• Edge AI for onsite decisions • AI safety analytics via wearables
Drones & Computer Vision	• Automated inspections • Safety risk alerts • Material & stock tracking	• 60% faster monitoring • Cuts manual checks • Enhances quality control	• Urban flight restrictions • Weather impacts data collection	• Autonomous drone fleets • AI defect detection & audits
Digital Twins	• Project simulation • Anomaly & workflow optimization • Automated construction	• 35% better timeline forecasts • 20% less waste • Real-time adjustments	• High processing demands • Hard to integrate with old systems	• Self-optimizing sites via AI • Scenario-based ML risk analysis

B. BENCHMARKING ADOPTION ACROSS SECTORS

The cross-sector adoption of ML and big data highlights stark disparities, offering both insight and caution for construction applications. Manufacturing and healthcare demonstrate mature use of predictive maintenance and resource optimization, aided by centralized data and standardized workflows—advantages largely absent in the fragmented, project-specific construction sector[16], [42]. Nonetheless, certain strategies are transferable. Real-time data pipelines and adaptive learning frameworks from industry inform logistics and tracking in construction. While ML integration lags, the core techniques are sector-agnostic; the key differences lie in implementation context and digital readiness.

Table 4 compares ML use across sectors, showing that models like RF, XGBoost, and LSTM—successful in healthcare and finance—have promising applications in construction if tailored to domain-specific constraints. For instance, RF models used in fraud detection adapt well to cost and defect prediction, though dependent on data quality. Similarly, smart-city sensor models support construction monitoring, albeit with challenges in calibration and real-time processing.

However, transferring models across domains faces limits. Construction's inconsistent data, site variability, and automation resistance constrain the use of models designed for standardized environments. Hybrid methods (e.g., fuzzy logic with reinforcement learning) aim to boost adaptability, but empirical validation remains limited.
The literature also lacks longitudinal studies on model evolution across projects and offers little insight into how organizational culture, especially in risk-averse firms, affects cross-sector AI adoption. Thus, despite technical feasibility, progress depends on leadership, digital skills, and policy frameworks.

In sum, while cross-industry benchmarking reveals valuable lessons, effective transfer requires contextualization through pilot programs that reflect construction's unique operational and cultural dynamics.

Table 5 Cross-industry analysis of ML models

ML Model	Effectiveness in Other Industries	Effectiveness in Construction	Improvements for Construction	Hybrid Model Potential
Sensor-Based Approach	Predictive maintenance, smart cities	Structural & equipment monitoring, safety	Enhance data fusion	ML + rules for proactive maintenance
RF (Random Forest)	Fraud detection, risk scoring	Cost, demand, defect prediction	Improve feature selection	RF + genetic algorithms for optimization
Fuzzy Bayesian Network	Diagnosis, cybersecurity, supply chain	Risk, accident estimation, decision support	Merge real data with models	Bayesian + Monte Carlo for risk scheduling

ML Model	Effectiveness in Other Industries	Effectiveness in Construction	Improvements for Construction	Hybrid Model Potential
Fuzzy AHP	MCDM in logistics, healthcare	Contractor ranking, project selection	Automate weight tuning	FAHP + RL for adaptive planning
YOLO	Driving, surveillance, checkout automation	Site safety, defect detection	Train on domain-specific data	YOLO + IoT for hazard alerts
LLMs	Contracts, reports, customer service	Document analysis, AI-generated reports	Fine-tune on construction texts	LLM + rules for compliance
GNNs	Fraud, social networks, recommendations	Complex dependency modeling	Refine node embeddings	GNN + RL for scheduling
LSTM	Forecasting, speech	Delay, cost prediction, sensor trends	Add attention for long-term dependencies	LSTM + constraint optimization
GANs	Image synthesis, augmentation, anomaly detection	Synthetic safety training data	Stabilize with progressive training	GAN + CV for defect detection
XGBoost	Credit, diagnostics, fraud	Cost, forecasting, productivity	Feature selection + optimization	XGBoost + heuristics for estimation
Deep Q-Learning	Robotics, traffic, optimization	Equipment autonomy, fleet scheduling	Use replay and reward shaping	DQN + heuristics for crane ops
SVM	Bioinformatics, handwriting	Defect & material classification	Optimize kernels	SVM + DL for real-time classification
RNN	Speech, stock, NLP	Forecasting, anomaly detection	Add attention	RNN + Bayesian for risk prediction
Autoencoders	Anomalies, compression, features	Defect, safety monitoring	Use diverse datasets	Autoencoder + GAN for simulations
Transformers	NLP, diagnostics, vehicles	Documentation, risk analysis	Fine-tune on domain data	Transformer + GNN for compliance
RL (Reinforcement Learning)	Robotics, traffic, gaming	Scheduling, resource use	Multi-agent coordination	RL + Digital Twin for site control
Capsule Networks	Imaging, object recognition, fraud	Hazard and defect detection	Train on 3D data	Capsule + LiDAR for spatial safety
Hierarchical Clustering	Segmentation, genomics, traffic	Workforce & material grouping	Use dynamic linkage	Clustering + RL for task scheduling
Diffusion Models	Synthetic data, design, anomalies	AI-assisted simulation design	Train on diverse architecture data	Diffusion + GANs for AI design

CHALLENGES IN ADOPTION

The successful deployment of ML and big data in construction is hindered not only by technical limitations but also by organizational inertia and regulatory ambiguity. The reviewed literature identifies four broad categories of barriers: data quality and processing, algorithmic complexity, workforce capability, and ethical or legal constraints. These factors are not isolated; rather, they interact across project, firm, and industry levels, compounding the resistance to AI-driven transformation.

A. TECHNICAL CHALLENGES

Data Quality and Processing Issues

Construction generates vast amounts of heterogeneous data from sensors, BIM systems, and project management tools, yet this data is often inconsistent, incomplete, or unstructured, limiting its value for model training and real-time inference[43]. AI-based preprocessing and anomaly detection can improve data quality but rely on well-labeled datasets and seamless system integration. Emerging solutions like federated learning and blockchain-based data sharing[39] show potential but face limited adoption due to concerns over scalability, interoperability, and cybersecurity.

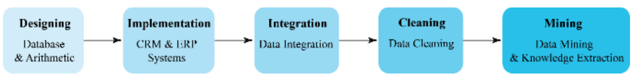

Figure 7 Data processing flow

Algorithm Complexity and Computational Requirements

Advanced ML models like Mask R-CNN and GANs require substantial processing power and memory, limiting their feasibility on typical construction sites[44]. Decentralized systems, such as public blockchains, further exacerbate latency and cost issues[45]. While edge computing and cloud platforms are often proposed as alternatives, their total cost of ownership and viability in low-connectivity environments remain underexplored.

B. ORGANIZATIONAL CHALLENGES

Resistance to Change

Cultural conservatism remains a key barrier to technological adoption in construction. Firms often adhere to legacy practices and hierarchical decision-making, showing reluctance toward data-driven tools[16]. This resistance stems from limited awareness of AI's benefits, fears of job loss, and perceived implementation complexity. Suggested countermeasures—such as pilot projects, stakeholder engagement, and policy incentives—are promising, but empirical evidence on their impact in transforming organizational culture remains limited.

Lack of Skilled Personnel

A major barrier to ML adoption is the talent gap. Many construction professionals lack the computational skills needed to select, tune, or interpret ML models. In BIM deployments, insufficient technical training is a key risk for failure[46], especially in smaller firms that cannot afford dedicated data scientists. While certifications and interdisciplinary education have been proposed, few are integrated into formal construction curricula. Industry-academia partnerships are encouraged, but their scalability and relevance to the field remain underexamined.

Cost Barriers

High implementation costs—including infrastructure, licensing, and training—remain a major barrier, particularly for SMEs[47]. Costs are further amplified in blockchain or sensor-intensive applications due to high initial investment and ongoing maintenance demands[48]. While AI-as-a-Service (AIaaS) and innovation grants offer potential support, their accessibility is uneven, and the literature lacks robust cost-benefit analyses or financing strategies suited to the construction sector.

C. ETHICAL, LEGAL, AND REGULATORY CHALLENGES

Data Privacy Concerns

The growing use of surveillance technologies—such as wearables and drones—on construction sites raises ethical concerns around consent, monitoring, and data governance[49], [50]. These issues are compounded by the presence of multiple actors with varying data policies. Federated learning and blockchain-based access controls offer privacy-preserving solutions[51] (see Figure 8), but remain experimental and face barriers in digitally immature environments. Furthermore, major regulatory frameworks like GDPR and CCPA are rarely addressed in industry guidelines, highlighting a significant policy gap.

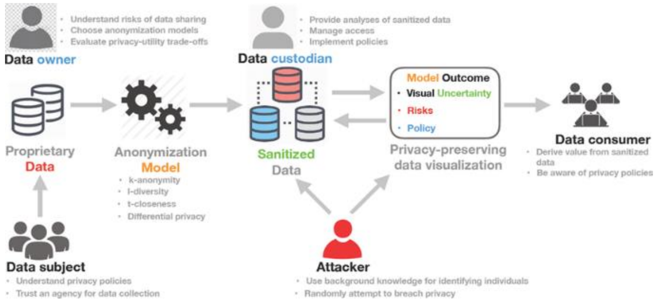

Figure 8 Data flow and roles of privacy stakeholders[51]

Ethical AI Usage

The opacity of complex ML models poses risks, as unaddressed data bias can lead to unfair outcomes in labor scheduling or safety monitoring[52] (Debrah and others 2022). In green construction, "black-box" models may erode stakeholder trust by obscuring trade-offs between sustainability, cost, and time. To improve accountability, researchers advocate for Explainable AI (XAI), bias auditing tools, and AI ethics committees within firms[53]. Yet, these measures remain largely untested and are rarely implemented beyond pilot programs.

Compliance Issues

The construction industry's fragmented regulatory environment hinders the adoption of AI. Technologies like blockchain and IoT often span jurisdictions and are incompatible with legacy systems[54], [55]. The lack of unified standards for data storage, transmission, and algorithm certification limits scalability. While global governance frameworks and smart contract-based compliance are proposed, most discussions remain theoretical, with little evidence of industry-wide coordination or enforcement, highlighting a persistent gap between innovation and policy.

DISCUSSION

A. PROPOSED ADOPTION FRAMEWORK

To address the limitations in the current implementation of ML and AI solutions in the construction sector, particularly in resource allocation and risk management, we propose two frameworks in this section. These frameworks provide clear steps for implementing ML-powered solutions to ensure proactive risk management and mitigation, as well as an AI-driven solution for resource allocation.

AI-Enhanced Construction Risk Prediction and Mitigation Framework

Implementing AI and big data in construction risk management involves a structured approach to data integration, predictive modeling, and stakeholder collaboration. Figure 9 presents a step-by-step AI-enhanced construction Risk Prediction and Mitigation Framework. It combines predictive analytics, IoT-enabled monitoring, and collaborative tools to anticipate and mitigate risks in construction projects.

The framework addresses the challenges of ML applications in construction by integrating historical and real-time data from diverse sources, such as IoT sensors, weather forecasts, and supply chain logs, into a centralized data lake. This approach overcomes the issue of data silos and unstructured data by standardizing formats and ensuring data quality through cleansing tools (like Talend). Predictive models, trained using ML algorithms (e.g., TensorFlow, Azure ML Studio), forecast risks such as delays, cost overruns, and safety incidents, enabling proactive mitigation. Real-time monitoring systems, powered by IoT and AI, provide continuous oversight of site conditions, equipment health, and worker safety, reducing the reactive nature of traditional risk management. By fostering stakeholder collaboration through centralized dashboards (e.g., Autodesk construction cloud, Oracle Aconex) and training programs (e.g., Coursera for business), the framework ensures that AI-generated insights are effectively communicated and acted upon, enhancing trust and adoption across teams. By embedding iterative feedback loops and compliance checks, the framework enables continuous refinement of predictive models and ensures alignment with ethical standards. Post-project reviews enhance model accuracy, while regular audits safeguard fairness and adherence to frameworks such as ISO 31000. Finally, by integrating AI tools with enterprise risk management platforms and expanding into emerging use cases, the framework supports scalable adoption across organizational functions. This ensures that AI-driven insights align with strategic goals while extending value to areas such as contract compliance and sustainability.

However, the framework is not without limitations. High implementation costs and the complexity of integrating AI tools with legacy enterprise systems pose significant challenges, with 40% of firms experiencing delays in achieving the return on investment due to integration hurdles. Despite these limitations, the framework represents a transformative approach to construction risk management, offering long-term efficiency and safety improvements for those able to navigate its initial barriers.

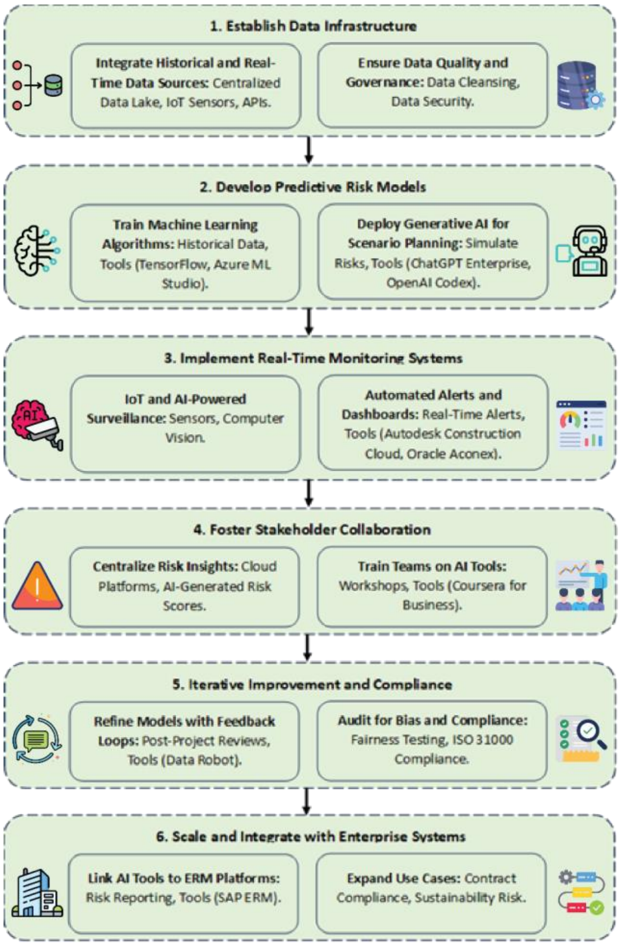

Figure 9 AI-Enhanced Construction Risk Prediction and Mitigation Framework

Smart Build: AI-Optimized Resource Management for Construction Projects

In the area of resource allocation, the next framework in Figure 10 presents an AI-driven construction Resource Allocation structured approach that leverages AI, IoT, and predictive analytics to optimize resource management in construction projects. It integrates fragmented data sources (e.g., enterprise resource planning (ERP) systems, IoT sensors) into a unified platform, enabling real-time tracking of materials, equipment, and labor. Predictive models forecast resource demands, while dynamic optimization engines automate reallocation based on real-time data. Stakeholder collaboration is enhanced through centralized dashboards, and iterative feedback loops ensure continuous improvement. This framework transforms traditional, static resource planning into an agile, data-driven process, improving efficiency and reducing waste.

The AI-Driven Dynamic Resource Allocation Framework tackles the challenges of ML in construction by creating a unified data infrastructure that integrates fragmented data sources, such as ERP systems, IoT devices, and material delivery logs. This integration enables the development of predictive models (e.g., TensorFlow, SAP ERPsim) that forecast resource needs and simulate allocation scenarios, addressing the issue of resource inefficiency. Real-time tracking of resources through IoT and radio frequency identification (RFID) tags, combined with AI-powered scheduling tools (e.g., Oracle P6, Synchro), allows for dynamic optimization of labor and equipment allocation, reducing idle time and costs. The framework also emphasizes stakeholder collaboration through centralized dashboards (e.g., Procore, Autodesk Construction Cloud) and training programs (e.g., Coursera courses), ensuring that teams can interpret and act on AI-driven recommendations. By incorporating feedback loops (e.g., DataRobot) and bias audits (e.g., IBM AI Fairness 360), the framework ensures continuous improvement and ethical use of AI, overcoming resistance to change and potential algorithmic biases. By scaling integration with enterprise systems such as SAP, the framework aligns resource planning with broader financial and operational strategies, while expanding AI applications to areas like sustainability monitoring and proactive safety resource allocation.

The framework offers significant benefits, including a potential reduction in resource idle time, cost savings through optimized material orders, and improved productivity via AI-optimized labor assignments. It enhances decision-making with real-time insights and fosters collaboration among stakeholders. However, it also has limitations: integrating legacy systems (e.g., Excel-based schedules) can be challenging, and the upfront costs for IoT sensors and AI tools are high. Resistance to change from teams unfamiliar with AI and potential algorithmic biases (e.g., prioritizing cost over safety) represents an additional hurdle. Addressing these challenges is critical for successful implementation.

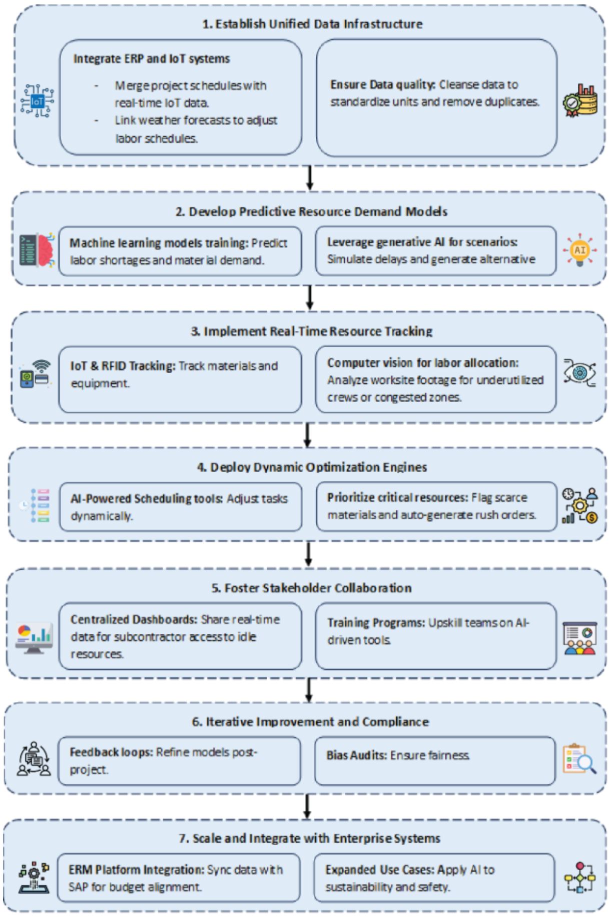

Figure 10 Smart Build: AI-Optimized Resource Management for Construction Projects

D. IMPLEMENTATION ROADMAP OF THE FRAMEWORKS IN THE CONSTRUCTION INDUSTRY

With construction industry being slow in technology adoption and several barriers discussed earlier, this roadmap provides a structured, phased approach to overcoming these barriers and facilitating widespread AI adoption in construction projects for risk mitigation and resource optimization. Drawing lessons from various industries as Table 6, this roadmap provides a step-by-step guide for construction firms to follow a similar trajectory—from AI exploration to full-scale deployment—while ensuring regulatory compliance, workforce readiness, and technological standardization.

E. CONCEPTUAL VALIDATION AND ALIGNMENT WITH STANDARDS

Given the absence of empirical testing in this study, a dual validation strategy is adopted to assess the robustness and applicability of the proposed frameworks: (i) theoretical grounding based on existing literature, and (ii) alignment with established industry standards and international guidelines. This approach ensures that the frameworks are both scientifically sound and practically relevant.

AI-Enhanced Construction Risk Prediction and Mitigation Framework

The AI-Enhanced Construction Risk Prediction and Mitigation Framework (Figure 9) is anchored in proven approaches from construction informatics and predictive analytics. The integration of real-time and historical data from IoT sensors, weather feeds, and supply chain logs reflects best practices in risk-aware construction planning[56], [57], [58]. The use of predictive modeling for anticipating cost overruns and safety incidents has been extensively studied in recent work[59], while the emphasis on stakeholder dashboards and collaborative platforms aligns with digital transformation trends in construction risk governance[60], [61]. Furthermore, the incorporation of feedback loops and ethical audit mechanisms reflects emerging consensus on responsible AI deployment in safety-critical industries.

The Smart Build: AI-Optimized Resource Management Framework (Figure 10) similarly draws from validated AI and IoT applications in construction logistics. Real-time tracking of materials and labor using RFID, combined with ERP integration, is a well-documented strategy for improving construction productivity and reducing idle time[62], [63]. Predictive forecasting and AI-based scheduling techniques have shown strong performance in optimizing resource flows under uncertainty[64], [65]. Finally, the framework's integration of bias auditing and iterative improvement mechanisms aligns with practices in AI lifecycle management across industrial contexts[66], [67].

Alignment with International Standards and Best Practices

Both frameworks are designed to conform with globally recognized standards in risk management, project governance, and ethical AI design:

1. ISO 31000 (Risk Management): The risk mitigation framework follows the ISO 31000 process—risk identification, assessment, treatment, monitoring, and review—ensuring procedural consistency in enterprise risk governance.
2. PMBOK Guide (Project Management Institute): Core elements of both frameworks (resource planning,

stakeholder communication, risk response) are in line with the PMBOK knowledge areas, particularly in integration, resource, and risk management domains.
3. ISO/IEC 38507:2022 and IEEE Ethically Aligned Design: The inclusion of bias audits (e.g., IBM AI Fairness 360), explainability mechanisms, and post-project review loops directly support the principles of transparency, accountability, and non-discrimination promoted by AI governance standards.
4. ISO 19650 (Information Management in BIM Environments): The proposed use of centralized dashboards and digital platforms for collaboration supports compliance with ISO 19650's principles for structured, secure, and interoperable information flows across construction project lifecycles.

F. RECOMMENDATIONS FOR FUTURE APPLICATIONS

Based on our analysis, we have identified several limitations in the application of ML and big data techniques within the construction sector. To address these gaps, we recommend the following model applications that hold significant future potential in Table 7:

Table 6 Implementation Roadmap for the Construction Industry

Phase	Objective	Key Actions	Expected Outcomes
Phase 1: Foundational Readiness & Awareness (0–6 months)	Build foundation by addressing knowledge gaps, data readiness, and stakeholder alignment.	• Conduct training • Assess data infrastructure • Align key stakeholders • Develop privacy and ethics guidelines	• Greater AI awareness • Roadmap for integration • Industry commitment to data-driven practices
Phase 2: Pilot & Proof of Concept (6–18 months)	Test AI in real projects to assess feasibility and integration.	• Launch pilot projects for risk/resource use • Integrate with BIM, IoT, digital twins • Benchmark vs. traditional methods • Collect feedback • Refine models for site/data diversity	• Demonstrated feasibility • Performance benchmarks • Enhanced model accuracy
Phase 3: Standardization & Scaling (18–36 months)	Scale adoption across projects with compliance and skills development.	• Create data-sharing & security standards • Establish regulations • Deploy digital twins for monitoring • Continue workforce training • Extend AI to supply chain & maintenance	• Widespread AI use • Compliance & data security • Skilled workforce
Phase 4: Innovation & Continuous Improvement (36+ months)	Make AI a standard and drive ongoing innovation.	• Set AI governance • Foster R&D partnerships • Explore robotics & generative AI • Develop global benchmarks	• Autonomous AI systems • Global AI standards • Ongoing gains in efficiency and safety

Table 7. Comparison of existing AI models and emerging AI models in the construction sector

Category	Existing Models	New & Emerging AI Models
Risk Prediction & Mitigation	SGRU, LSTM-based predictive models	LLMs (GPT-4, Llama, DeepSeek) with real-time adaptive learning
Resource Optimization	YOLO, Faster-RCNN for object recognition	ViT, Swin-Transformer
Automated Progress Monitoring	VR-based tracking, Point Cloud methods	AI Habitat (Meta), Matterport-driven datasets
Ergonomic Risk Management	RULA, REBA, OWAS, Kinect-based motion tracking	AI-powered multi-modal motion tracking, Transformer-based pose estimation, Wearable AI
Cost Prediction	Regression models (OLS, SVR), Monte Carlo simulation, ANN-based cost estimators	LLM-assisted multi-source models integrating news, weather, economic trends, and blockchain data
Object Detection & Monitoring	YOLO, Faster-RCNN	DETR-based models, 3D Vision Transformers, Neural Radiance Fields

CONCLUSIONS

Integrating ML and hybrid approaches presents transformative potential for risk management and resource optimization in construction. This review screened 5,756 initially identified records and retained 154 eligible studies, of which 59 high- and moderate-quality studies were included in the detailed synthesis after quality assessment. The reviewed evidence shows that ML and big data approaches can improve construction decision-making, with representative studies reporting prediction accuracies of up to 93.75% for delay-risk prediction and 97.6% for equipment matching. These findings indicate that data-driven tools can support more proactive risk detection, more accurate forecasting, and more efficient allocation of labor, materials, and equipment.

The readiness-level assessment further indicates that ML and big data applications in construction are progressing beyond purely conceptual development, but have not yet reached consistent industry-wide deployment. Low-readiness studies mainly correspond to conceptual models, laboratory-stage methods, or early algorithmic demonstrations. Medium-readiness studies are more common and typically involve pilot applications, simulated environments, controlled case studies, or validated prototypes. High-readiness studies are present but less dominant, generally involving field deployment, real-time monitoring, or demonstrated use in practical construction settings. Overall, the reviewed evidence suggests that most synthesized studies demonstrate medium-to-high readiness, confirming the practical potential of ML and big data tools while also highlighting a persistent gap between technical model performance and scalable implementation in real construction projects.

Adoption varies globally: advanced regions benefit from stronger digital infrastructure and supportive policy environments, whereas developing regions face greater cost, infrastructure, and readiness challenges. Barriers such as high implementation costs, skill gaps, data privacy concerns, and resistance to change require scalable, user-centric, and ethically governed solutions. Future research should focus on longitudinal field validation, standardized ML evaluation metrics, interoperable data protocols, explainable AI, and cost-effective deployment strategies. With these foundations, the construction industry can better harness ML and big data to improve safety, efficiency, and sustainability.

A. RESEARCH LIMITATIONS

This review has several limitations:

1. The scope is limited by database access and language; notably, studies from CNKI (China) were excluded.
2. Many reviewed studies use proprietary or small datasets, limiting generalizability.
3. ML model performance varies widely due to differences in datasets, metrics, and validation, making comparisons difficult.
4. Some studies may overstate AI effectiveness due to funding bias or selective reporting.

B. RESEARCH GAPS AND FUTURE DIRECTIONS

Despite notable progress, key research gaps persist. Current AI systems largely depend on historical data and lack autonomy in dynamic construction environments. Future efforts should focus on adaptive agents capable of real-time decision-making, automated contingency planning, and proactive risk detection through technologies such as AI-enabled drones and reinforcement learning. Ethical concerns also remain critical, as biased datasets may produce opaque or unfair outcomes. Research must prioritize explainable, auditable AI with legal accountability frameworks, particularly in safety and workforce management. Scalability is another limitation; models often function in isolation, underscoring the need for cross-project learning and AI-driven procurement that adapts to real-time risks and supply changes. Emerging tools like quantum computing may further enhance large-scale planning. Finally, safety monitoring must evolve beyond motion tracking by integrating multimodal data, such as biometrics, thermal inputs, and emotion recognition, delivered via wearable AI systems to detect latent hazards and provide ergonomic feedback in real time.

Conflicts of Interest: The authors declare no conflict of interest.

AI usage Statement: During the preparation of this work, the authors used ChatGPT-4o to improve the readability of the manuscript. After using this service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Data Availability Statement: Data sharing does not apply to this article as no new data were created or analyzed in this study.

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