International Journal of Applied Smart Interdisciplinary Technologies (IJASIT)

Home Page: https://ijasit.org **ISSN: 3139-759X**

https://doi.org/10.68104/ijasit.v1.i4.55

IoT-Enabled Real-Time Construction Project Monitoring and Predictive Management System for Schedule, Cost, and Resource Optimization

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Article History:
Received Date: 20 September 2026
Revised Date: 16 October 2026
Accepted Date: 21 October 2026
Published Date: 04 November 2026

Keywords:

Internet of Things (IoT); Construction 4.0; Predictive Analytics; Machine Learning; Building Information Modeling (BIM); Digital Twins; Earned Value Management (EVM); Project Controls

ABSTRACT

In the construction industry, severe schedule and cost overruns, retrospective performance tracking, and fragmented communication are persistent problems. The Construction 4.0 paradigm has encouraged a trend toward data-driven, real-time project management that depends on the Internet of Things (IoT), artificial intelligence (AI), and building information modelling (BIM). This systematic evaluation, which focuses on multidimensional resource optimization, schedule, and cost, critically evaluates the use of IoT technology into construction project management. By combining content primarily released between 2019 and 2026, the analysis looks at how continuous sensor data transforms traditional, reactive management frameworks—such as Earned Value Management (EVM) and the Critical Path Method (CPM)—into proactive, predictive control systems. Evidence indicates that while individual sensor technologies and machine learning delay-prediction algorithms have reached a high degree of maturity, there are currently few comprehensive platforms connecting these various data silos. This paper outlines a comprehensive nine-layer conceptual framework for fully integrated predictive construction management, identifies major implementation challenges, and explains sensor architectures, predictive models, and digital twin integrations that are revolutionizing the sector.

1. Introduction

The global construction industry is continuously plagued by structural inefficiencies, productivity bottlenecks, and persistent cost overruns, despite being a significant driver of economic growth. Over 85% of large-scale infrastructure projects exceed their initial delivery deadlines, leading to budget overruns and compounding fines, according to estimates from throughout the world [1]. Construction project management has historically relied heavily on human data collection, static scheduling systems, and retrospective financial reporting. It is nearly impossible for site managers to act promptly with these traditional procedures because of the inherent significant temporal gaps between administrative awareness and actual field implementation.

Construction 4.0, which applies Industry 4.0 concepts to the built environment, seeks to address these inefficiencies by extensive site digitalization [2]. This paradigm shift requires the integration of advanced analytical engines with actual construction environments. The Internet of Things (IoT), autonomous robotics,

and Building Information Modeling (BIM) are a few examples of technologies that establish a cyber-physical ecosystem where digital models constantly reflect the physical state of the site [3]. The primary sensory layer in this system is IoT. Integrating linked sensors into buildings, materials, machinery, and personal protective equipment (PPE) enables continuous site operations visibility [4].

Despite the Internet of Things' rapid expansion, the process of transforming raw sensor data into practical project control insights is still highly fragmented. Deployments, like wearables for safety or drones for development, frequently operate in distinct functional silos without integrating into basic scheduling and cost software frameworks [5]. One major research need is the complete synthesis of real-time IoT data with predictive analytics to achieve simultaneous schedule, cost, and resource optimization [6]. This systematic study addresses key research issues, such as mature sensing technologies, AI/ML predictive integration, deployment challenges, and project performance impacts, and produces a nine-layer conceptual framework for fully integrated predictive construction project management.

2. Review Methodology

To ensure analytical rigor and systematic repeatability, our work employed a systematic scoping review approach that closely followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2020 requirements [7]. Google Scholar was employed as a secondary method for gathering gray literature, while primary database searches concentrated on significant scientific archives like Scopus, Web of Science, ScienceDirect, IEEE Xplore, and SpringerLink. Complex Boolean strings that combined keywords like ("Internet of Things" OR "IoT" OR "Sensor*") AND ("Construction Project Management" OR "Schedule Optimization" OR "Cost Control") AND ("Artificial Intelligence" OR "Machine Learning" OR "Digital Twin") were used in the search strategy.

In order to capture the most pertinent cutting-edge Construction 4.0 advances, the temporal scope was strictly restricted to 2019–2026. Strict inclusion requirements had to be met by eligible studies: they had to be published in peer-reviewed English journals and specifically examine IoT applications during physical building with a focus on resource, time, or cost optimization. Excluded were studies that only addressed facility management, non-project sensor engineering, or non-peer-reviewed commentary.

The first search produced 1,248 records from primary databases (Scopus: 312, Web of Science: 286, ScienceDirect: 221, SpringerLink: 153, IEEE Xplore: 148, Google Scholar: 118), in addition to 32 additional records from reference mining and gray literature, as shown in the PRISMA flow diagram for literature screening (Figure 1). 1,012 distinct records were subjected to title and abstract screening after 268 duplicates were eliminated. As a consequence, 735 irrelevant records were eliminated. After then, 277 full-text papers were evaluated for eligibility; 186 of them were eliminated for various reasons, including not meeting inclusion criteria or not having enough methodological information. In the end, the final qualitative synthesis had 91 peer-reviewed studies.

Functional applications and technical convergence were used to further categorize the collected material. The bibliometric distribution (Figure 2) shows that publications on IoT and BIM integration increased steadily between 2019 and 2025, with a significant increase in AI-related research starting in 2021. The conceptual relationships between machine learning, digital twins, BIM, and cost/schedule controls are highlighted by network keyword co-occurrence analysis (Figure 3). Lastly, Figure 4 illustrates a balanced emphasis on schedule, money, resources, and safety by mapping the distribution of these reviewed studies across important Construction 5.0 application areas.

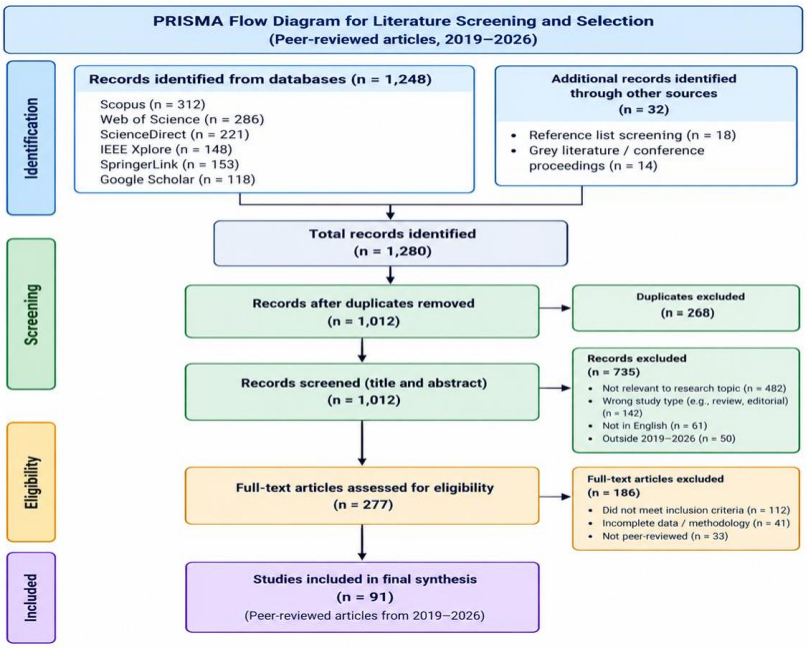


Fig. 1. PRISMA-style literature screening and selection flow diagram

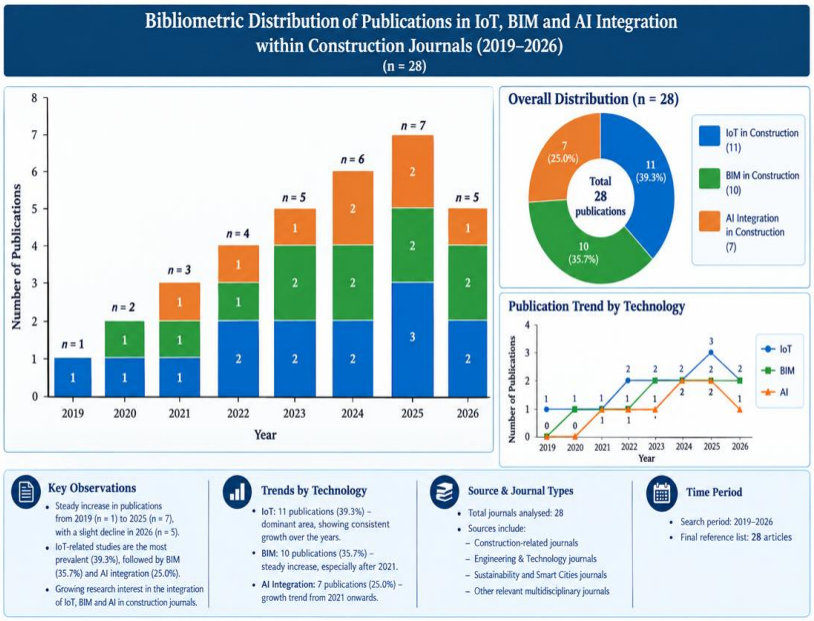


Fig. 2. Research trend by publication year

3. Fundamentals and Real-Time Monitoring of IoT-Enabled Construction

An IoT-enabled building site's architectural topology is arranged into hierarchical tiers intended for real-time data gathering, transmission, and analysis. Heterogeneous sensor networks dispersed throughout the site environment serve as the foundation for the perception layer [9]. Inertial Measurement Units (IMUs) embedded in wearables to assess labor posture and safety dynamics, GPS/GNSS modules for heavy equipment positioning, Active and Passive RFID tags for automated material tracking, and Ultra-Wideband (UWB) and Bluetooth Low Energy (BLE) beacons for sub-meter indoor workforce localization are some of the key technologies. Industrial communication networks send continuous sensor payloads to hybrid edge and cloud

computation nodes using LoRaWAN long-range protocols and 5G ultra-reliable low-latency connections. While edge computing handles critical safety alerts locally, cloud systems compile time-series data into centralized repositories for high-level project analytics.

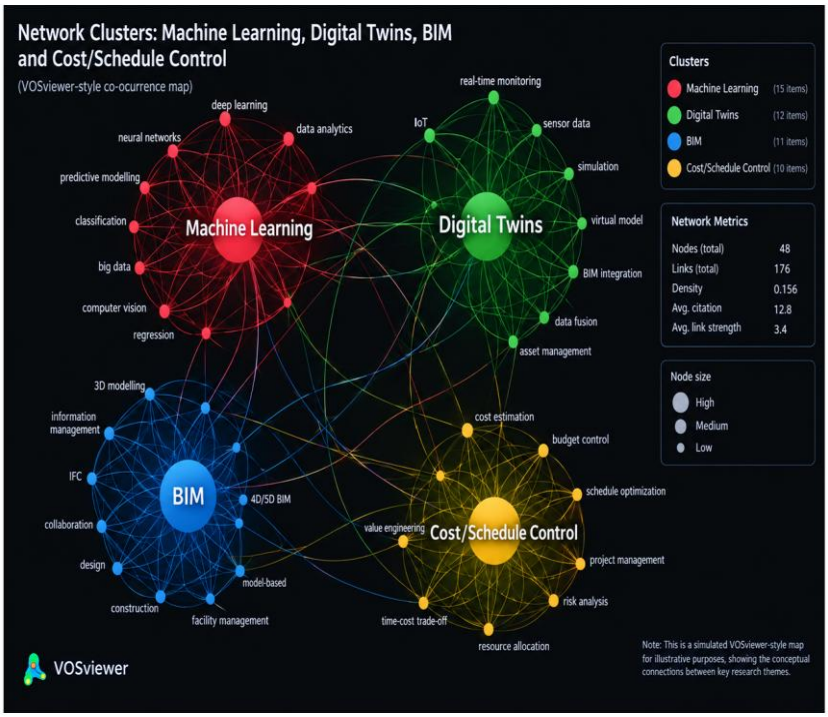


Fig. 3. Keyword co-occurrence / network analysis

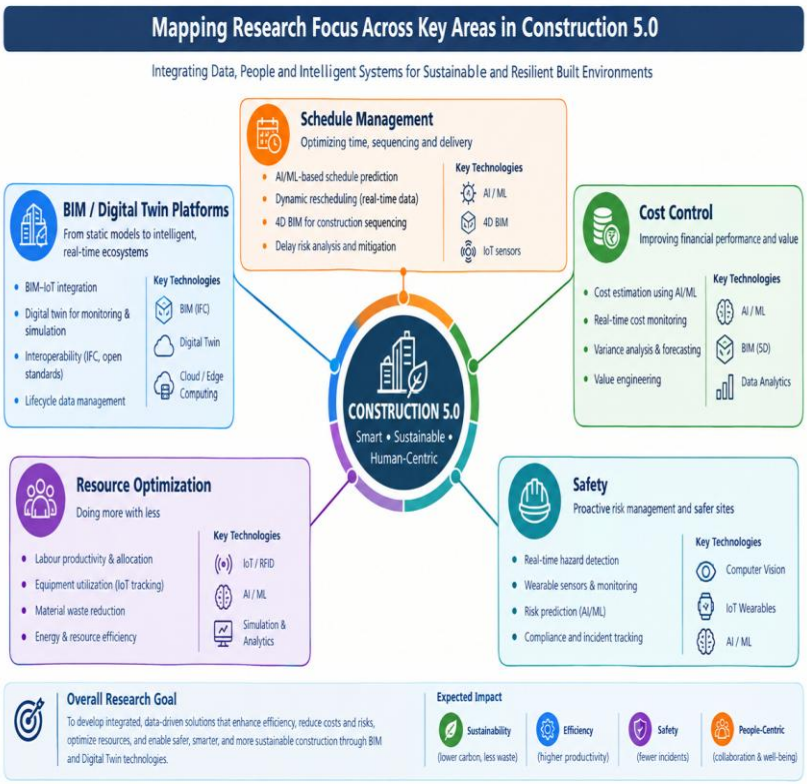


Fig. 4. Distribution of reviewed studies by application area

The real-time visibility needed for multi-dimensional site monitoring is provided by this reliable sensing infrastructure. Drone-captured photogrammetry and 4D BIM are used in progress monitoring to automatically identify volumetric differences between as-built and as-planned conditions. Site density management and attendance verification are made easier with RFID badges and smart hardhats for worker monitoring. By recording idle hours, fuel consumption, and engine diagnostics, equipment telematics reduce unrecorded downtime and initiate predictive maintenance. RFID-based material tracking lowers laydown loss and supply chain lag [10]. Additionally, UWB geo-fencing actively notifies workers to equipment zone violations, significantly reducing near-miss events, while environmental and geotechnical sensors monitor microclimatic effects on sensitive tasks (such concrete curing or crane lifting constraints).

The architectural topology of an IoT-enabled building site is organized into hierarchical tiers designed for real-time data processing, transmission, and collection. The perception layer is based on heterogeneous sensor networks distributed over the site environment [9]. Key technologies include Ultra-Wideband (UWB) and Bluetooth Low Energy (BLE) beacons for sub-meter indoor workforce localization, GPS/GNSS modules for heavy equipment positioning, Active and Passive RFID tags for automated material tracking, and Inertial Measurement Units (IMUs) embedded in wearables to evaluate labor posture and safety dynamics. Industrial communication networks use 5G ultra-reliable low-latency connection and LoRaWAN long-range protocols to transfer continuous sensor payloads to hybrid edge and cloud compute nodes. For high-level project analytics, cloud platforms aggregate time-series statistics into centralized repositories; edge computing manages urgent safety alarms locally.

The real-time visibility needed for multidimensional site monitoring is provided by this reliable sensing infrastructure. The end-to-end data pipeline, as shown in Figure 5, seamlessly moves from physical site sensors to edge processing and 5G gateways to cloud analytics and user dashboards. Drone-captured photogrammetry and 4D BIM are used in progress monitoring to automatically identify volumetric differences between as-built and as-planned conditions. Site density management and attendance verification are made easier with RFID badges and smart hardhats for worker monitoring. By recording idle hours, fuel consumption, and engine diagnostics, equipment telematics reduce unrecorded downtime and initiate predictive maintenance. RFID-based material tracking lowers laydown loss and supply chain lag [10]. Additionally, UWB geo-fencing actively notifies workers to equipment zone violations, significantly reducing near-miss events, while environmental and geotechnical sensors monitor microclimatic effects on sensitive tasks (such concrete curing or crane lifting constraints).

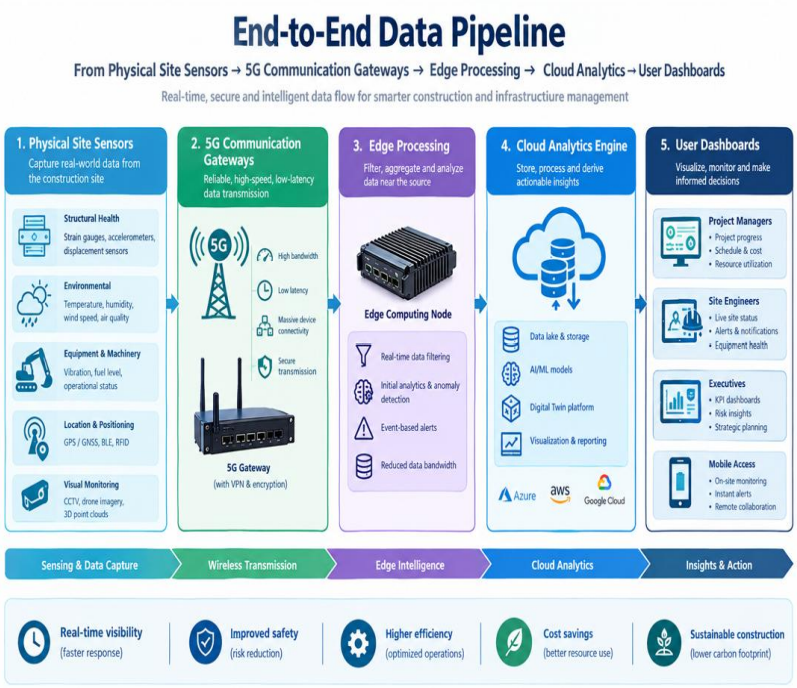


Fig. 5. Conceptual architecture of an IoT-enabled construction project monitoring system

Table 1
Key IoT technologies used in construction project management

Technology	Primary function	Construction application	Data generated	Advantages	Limitations
RFID (Active/Passive)	Proximity identification	Material tracking, inventory	Tag ID, timestamp, location zone	Low cost (passive), robust	Short range, line-of-sight issues
UWB (Ultra-Wideband)	High-precision tracking	Worker location, safety zones	Precise 3D coordinates	High accuracy (<10 cm)	High infrastructure cost
GPS / GNSS	Global positioning	Heavy equipment tracking	Geolocation coordinates	Excellent outdoor coverage	Fails indoor/underground
BLE (Bluetooth)	Localization / beacons	Tool tracking, access control	RSSI values, presence	Low power consumption	Signal interference on metallic sites
Computer Vision	Visual monitoring	Progress tracking, PPE detection	Video streams, image frames	Rich contextual data	High bandwidth requirement

4. IoT-Driven Project Controls: Schedule, Cost, and Resource Optimization

When dynamic field disruptions occur, the static, deterministic baseline structures of classic project control systems, such Earned Value Management (EVM) and the Critical Path Method (CPM), collapse [13]. These technologies are transformed into real-time operational control mechanisms via ongoing IoT feeds. IoT technologies identify schedule deviations early and anticipate downstream delays by automatically recording work execution through spatial-temporal sensor triangulation and machine learning-based activity identification. Predictive machine learning methods, for example, have been shown to anticipate delay risks with over 90% accuracy when tested on previous project datasets and schedule performance criteria [14]. Critical path dependencies are then probabilistically modified by rebaselining algorithms [15], and task delay is highlighted by dynamically updating 4D BIM models [16].

Figure 6 shows the structural data pipeline that transforms unprocessed physical data into these control dashboards. Additionally, Figure 7 shows how IoT data sample frequency and project performance are theoretically related, emphasizing how continuous high-frequency sampling significantly lowers managerial response latency as compared to batch techniques. IoT transforms cost control in finance management from delayed monthly billing reconciliations [17] to granular, real-time Activity-Based Costing (ABC). Direct inputs for EVM measurements are provided by continuous labor and equipment telemetry, which replaces subjective percent-complete estimations with sensor-verified Earned Value (EV) and Actual Cost (AC) characteristics [18]. Predictive algorithms relate daily cost burn rates to non-linear field performance in order to properly project Estimate at Completion (EAC) [19]. Furthermore, real-time sensing drives multi-resource optimization across labor, plant, and material supply networks in response to the operational objectives identified in organizational adoption frameworks [20]. Wearable analytics evaluates ergonomic strain to optimize worker rotation schedules, equipment telemetry allows trade contractors to share assets, and JIT material logistics eliminates the requirement for laydown yard storage. Accurate material ordering, reduced site scrap, and environmental compliance are all ensured via sensor tracking that complies with sustainable waste management criteria [21].

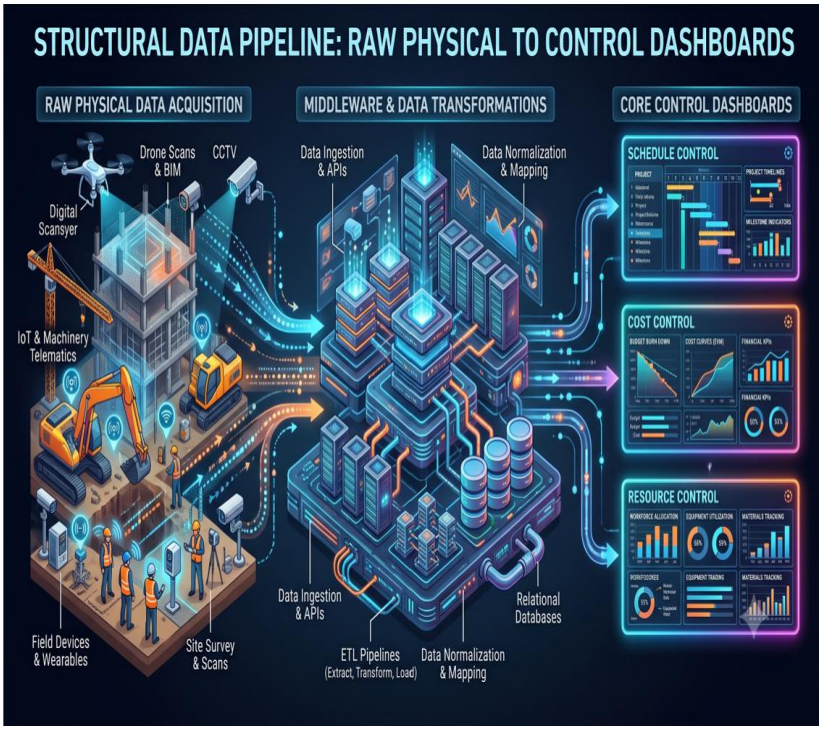


Fig. 6. IoT-to-project-management data flow

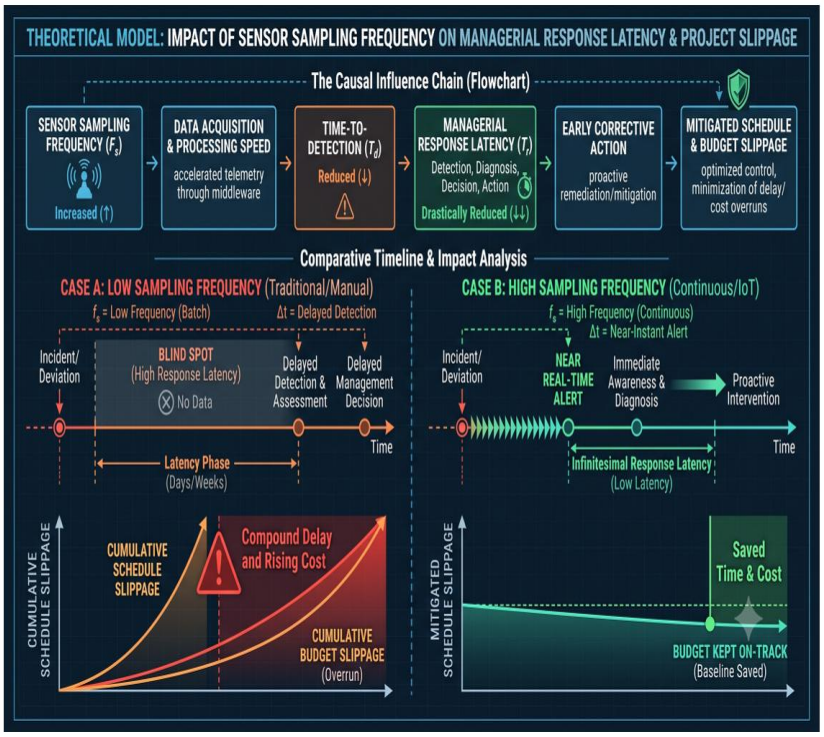


Fig. 7. Conceptual relationship between IoT data and project performance

Table 2
IoT applications across construction project-management functions

Management function	IoT application	Sensors/data source	Performance indicator	Reported benefit
Schedule	Activity duration tracking	Computer vision, UWB	Actual vs. Planned time	Automated delay identification
Cost	Idle time / waste reduction	Telematics, RFID	Resource utilization rate	Lower equipment rental costs
Safety	Geo-fencing hazardous zones	BLE beacons, GPS	Near-miss frequency	Proactive hazard alerts
Supply Chain	Just-in-time delivery	GPS tracking on trucks	Inventory turnaround time	Reduced on-site storage

Table 3
IoT-enabled schedule, cost, and resource management studies

Project type	Technology	Objective	Method	KPI	Main finding	Limitation
Commercial	ML + IoT	Schedule optimization	RF-PSO hybrid	Planning time reduction	Reduced planning time by 30%	Relied heavily on static datasets
Infrastructure	4D BIM + AI	Delay mitigation	Weather-integrated task modeling	Schedule variance	Proactive schedule adjustments	Requires high data maturity

5. Predictive Analytics, AI Integration, and Digital Twins

To transform unprocessed IoT data into predictive decision support, sophisticated AI and ML infrastructures are required [24]. Using constant cost-burn feeds and project attributes, supervised ensemble techniques like Random Forests (RF) are often utilized to predict cost overruns. While deep learning CNNs automatically scan visual drone data to assess site safety and structural progress, time-series architectures such as Long Short-Term Memory (LSTM) networks record temporal correlations across consecutive activity cycles to forecast timetable delays [14]. K-Means clustering and other unsupervised models are used to identify operational irregularities in daily labor productivity. Important risk features are selected by hybrid optimization frameworks such as Random Forest–Particle Swarm Optimization (RF-PSO) to increase prediction accuracy [22]. Moreover, Natural Language Processing (NLP) models mine safety text logs to map hazard probabilities [23].

Before making crucial decisions, managers can confirm recommendations thanks to Explainable AI (XAI) techniques, which provide transparent factor weightings to solve black-box opacity [25]. The ultimate goal of Construction 4.0 is multi-technology integration. Raw coordinate streams are transferred to certain semantic elements (such ISO 19650 IFC standards) when IoT and BIM are integrated. Expand this potential and model conceivable intervention scenarios before field deployment by establishing dynamic reflection between physical assets and bidirectional digital twins of virtual models [26]. Integrating GIS improves understanding of regional supply networks, while smart contracts on blockchain platforms start automated progress payments after IoT sensors verify installation milestones [8].

Table 4
Comparison of AI/ML techniques for predictive construction management

Algorithm	Prediction task	Input data	Output	Strengths	Limitations	Construction application
Random Forest	Cost overrun prediction	Project attributes, historical costs	Probability of overrun	High accuracy, feature importance	Less effective for time-series	Budget forecasting
LSTM Networks	Schedule delay forecasting	Continuous cycle times, weather	Predicted delay probability	Captures long-term sequential dependencies	High computational demand	Schedule optimization
K-Means Clustering	Productivity anomaly detection	Daily labor output	Clusters of abnormal days	Unsupervised, no labeled data	Struggles with non-linear relationships	Labor productivity

Table 5
IoT-BIM-Digital Twin integration

Integration type	Purpose	Data flow	Application	Benefits	Challenges
IoT + 4D BIM	Progress visualization	Sensor → API → BIM	Automated schedule updating	Eliminates manual data entry	Mapping sensor IDs to IFC elements
IoT + 5D BIM	Dynamic cost tracking	Sensor → ERP → BIM	Activity-based costing	Precise CPI tracking	High complexity in cost codes
DT + AI	Predictive simulation	Physical Site ↔ Digital Model	"What-if" analysis	Prescriptive decision support	High computational cost

6. Implementation Challenges, Research Gaps, and Future Directions

Integrating IoT and predictive technologies on active construction sites poses significant organizational, financial, and technical obstacles. Technical challenges include sensor hardware degradation under extreme site conditions (dust, vibration, and temperature), noisy or missing data streams that hinder machine learning performance, proprietary API silos that prevent interoperability across BIM, ERP, and scheduling software, and wireless packet loss in deep excavations [5]. Worker privacy concerns regarding wearable surveillance and cybersecurity risks associated with wireless data interception are the main causes of field-level opposition [27]. High initial capital costs deter small and medium-sized firms (SMEs) financially, while project managers' persistent lack of data science experience impedes organizational adoption. The literature still has a lot of unanswered questions. First, existing frameworks mostly focus on specific functional domains (such safety or material tracking) rather than fully integrated end-to-end control systems. Second, predictive models are still mostly based on static historical databases rather than dynamic, real-time IoT time-series streams. Third, current models struggle to accurately capture significant weather variables and unpredictable human behavior, and there are no clear empirical criteria for evaluating the financial Return on Investment (ROI) of full Digital Twin deployments. Future research must progress along critical technology vectors in order to address these limitations: [1] Federated Learning frameworks allow AI models to learn across multiple contractor datasets without revealing proprietary information; [2] smart contracts execute automated, sensor-verified EVM payments on blockchain ledgers; and [3] stochastic digital, which incorporates probabilistic modeling of human and environmental variability. Finally, while this analysis presents a thorough nine-layer model for predictive construction management (details in Section 7), it is important to remember that this is still a conceptual

framework. A significant constraint of current research is the absence of empirical validation for such end-to-end integrated systems. As a result, future research must prioritize the physical deployment of this framework through active job-site prototypes to confirm its practical usefulness, quantify actual return on investment (ROI), and fine-tune the layered integrations.

Table 6
Research gaps and future research opportunities

Research area	Existing limitation	Evidence from literature	Research gap	Recommended future direction
Predictive Analytics	Models trained on static data	[28]	Disconnect between live sensors and AI	ML models capable of dynamic reinforcement learning
Digital Twins	Focus primarily on geometric accuracy	[29]	Limited integration of behavioral uncertainty	Stochastic DTs that model human variables

Table 7
Challenges and barriers to real-world IoT deployment

Barrier	Technical impact	Project-management impact	Severity/evidence	Potential solution
Interoperability	Siloed data streams	Inability to cross-reference metrics	High	Adoption of open standards (IFC, ISO 19650)
Cybersecurity	Data breaches	Compromised safety systems	Critical	Blockchain integration for immutable logs
Skills Gap	Inability to maintain systems	Underutilization of data	Medium	Targeted workforce training, intuitive UIs

7. Conclusions

The Internet of Things has transformed construction management from reactive, retrospective tracking to proactive, predictive control. Sensing devices, such as RFID, UWB, and computer vision, can monitor labor, materials, and equipment. However, the real value lies in combining continuous IoT feeds with BIM, AI, and Digital Twins. Predictive solutions enable project managers to remove risks before they impact schedules or profit margins by utilizing Earned Value Management and automatic critical path updates. Overcoming technical interoperability limitations and labor skills Limitations will be critical in achieving completely automated, data-driven construction management.

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