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A BIM–IoT Integrated Framework for Smart Construction Sites: Application and Validation in Construction Management

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Abstract The continuing digital transformation of the construction industry has increased the need for construction-site management systems that can respond to complex, dynamic, and time-sensitive project conditions. Conventional management practices, which frequently depend on fragmented information, manual inspection, and delayed reporting, are increasingly insufficient for projects that require high levels of efficiency, safety, traceability, and data-supported decision-making. Building Information Modeling (BIM) provides an integrated digital representation of project geometry and information, whereas Internet of Things (IoT) technologies provide continuous sensing of personnel, equipment, environmental conditions, component status, and construction progress. Their integration therefore offers a practical basis for smart construction-site management. This paper proposes and validates a BIM–IoT integrated framework covering data acquisition, communication, fusion, storage, model updating, analysis, and visualization. The framework is developed to address recurring problems of limited interoperability, delayed information exchange, weak linkage between physical site conditions and digital models, and insufficient adaptability to construction-management scenarios. A project-based validation is conducted for quality management, schedule management, safety monitoring, panoramic video surveillance, and event traceability. Embedded sensors, positioning devices, mobile terminals, wireless networks, and cloud-based data services are used to collect and transmit site information, while three-dimensional and four-dimensional BIM models support spatial mapping, status updating, visual monitoring, and management feedback. The reported results indicate that the integrated solution improves inspection efficiency, issue-detection accuracy, schedule-deviation control, abnormal-event response, and historical-event retrieval relative to the traditional procedures used for comparison. The study demonstrates how a structured BIM–IoT architecture can support more timely, traceable, and visually integrated construction management while also identifying interoperability, scalability, and implementation complexity as continuing challenges for practical deployment.

Index Terms building information modeling, internet of things, smart construction site, integrated framework, real-time monitoring, construction management

I. Introduction

With the continuing digitalization and intelligent transformation of the construction industry, improving the management of projects throughout their life cycles has become an important concern for both researchers and practitioners [1], [2]. Construction sites are characterized by concurrent activities, multiple organizations, rapidly changing physical conditions, distributed resources, and strong interdependence among safety, quality, schedule, and cost objectives. Under such conditions, management approaches based primarily on paper drawings, periodic manual reporting, and experience-driven decision-making can lead to delayed information acquisition, fragmented data, weak traceability, and limited visibility of emerging risks [3]. These limitations affect not only construction efficiency and quality but also the ability of project teams to identify unsafe conditions, coordinate resources, and respond to deviations in a timely manner. Consequently, the development of data-driven mechanisms for real-time sensing, information sharing, visual coordination, and decision support has become an important component of construction-industry digital transformation [4], [5].

Building Information Modeling (BIM) has become a central technology in this transformation because it provides a structured digital representation of building geometry, component attributes, relationships, and project information. BIM supports design coordination, clash detection, construction simulation, schedule visualization, cost-related analysis, facility information management, and communication among project participants [6], [7]. Its value is also evident in performance-based construction and value-engineering applications, where model-centered information can support design evaluation, optimization, and project decision-making [4], [8]. Nevertheless, a BIM model does not automatically represent the continuously changing physical condition of a construction site. In many implementations, model information is updated through manual input or periodic synchronization, which limits the ability of BIM alone to provide continuous awareness of field conditions.

The Internet of Things (IoT) complements BIM by providing a technological infrastructure for sensing and transmitting dynamic information. Sensors, radio-frequency identification devices, positioning technologies, cameras, mobile terminals, and wireless communication networks can continuously capture information concerning environmental conditions, personnel locations, equipment states, material movement, and structural or component behavior. When IoT data are associated with corresponding BIM objects or spatial locations, the static or periodically updated digital model can be transformed into a more responsive representation of project conditions. Earlier reviews have identified BIM–IoT integration as a promising direction for improving construction and operational efficiency, while also emphasizing interoperability, integration architecture, data management, and implementation complexity as unresolved issues [10]. Applications in facility management and sustainable building operation further demonstrate that BIM–IoT integration can support data-driven monitoring beyond the construction phase [9], [15].

Recent studies illustrate the breadth of BIM–IoT applications. Hong and Guo developed a BIM–IoT application framework through multiple case studies and highlighted the need to address interoperability and implementation barriers [1]. Wang et al. proposed an integrated BIM–IoT framework for real-time construction quality monitoring by linking quality data to four-dimensional BIM [2]. Abdelalim et al. examined the combined use of BIM, employer information requirements, and IoT in facility management [3], while Kim et al. integrated point-cloud information, IoT sensing, and positioning technologies for construction monitoring [5]. Hu et al. developed a BIM-enabled digital-twin framework for real-time structural health monitoring based on wireless IoT sensing and structural analysis [6]. Other studies have investigated BIM–AIoT integration for green-building energy efficiency [7], BIM–IoT–FM integration for sustainable water management [9], and semantic integration of BIM, IoT, and data-mining technologies for energy-resilient buildings [13].

The literature also shows that the digital construction problem extends beyond sensing alone. IoT adoption is affected by technical, standardization, economic, knowledge, and complexity barriers [11]. Construction production planning requires coordination across multiple schedule levels [12], while information management and document traceability remain important for claims, disputes, quality records, and responsibility attribution [14], [26]. Smart-construction collaboration platforms have been proposed to integrate heterogeneous project information and automate construction-management processes [16]. BIM has also been applied to practical project-management tasks under intelligent-construction settings [17], and intelligent-construction management has been evaluated using multidimensional assessment models [18]. BIM–GIS integration provides an additional route for connecting building information with geographic context [19], whereas digital-twin and blockchain-based approaches have been explored to improve data governance and resilience [20], [23]. These studies collectively demonstrate substantial technical progress, but they also reveal that many solutions remain specialized around one application, one data source, or one project stage.

Quality management, schedule control, and site safety are particularly suitable for integrated digital support. A digital project-management framework can improve information utilization and coordination across project stages [21], while recent analyses of intelligent construction emphasize the importance of system integration, data interoperability, and alignment between technology and management processes [22]. Critical-factor studies of smart construction-site quality management likewise show that effective implementation depends on the coordinated treatment of technological, organizational, and management variables [24]. Standardized semantic and work-breakdown structures can strengthen the link between model objects and schedule or management information [25]. In addition, remote concrete-strength monitoring demonstrates how IoT sensing can be connected to digital platforms to support construction-quality decisions in real time [27].

Despite these developments, several limitations remain relevant to engineering practice. First, BIM and IoT platforms frequently use heterogeneous data models, interfaces, identifiers, and update frequencies, making consistent data mapping difficult. Second, many proposed systems are demonstrated at the prototype or subsystem level and therefore provide limited evidence of coordinated use across quality, schedule, safety, environmental monitoring, visualization, and traceability. Third, implementation may require multiple software tools, databases, cloud services, sensing devices, and communication protocols, increasing deployment and maintenance complexity. Fourth, integration performance must be considered not only from a technical perspective but also in terms of timeliness, reliability, model synchronization, traceability, usability, and practical management value. These limitations motivate a framework that treats BIM–IoT integration as a complete data and management workflow rather than as an isolated sensing or visualization task.

Accordingly, this paper proposes an engineering-oriented BIM–IoT integrated framework for smart construction-site management. The contribution is threefold. First, a systematic architecture is developed to connect field sensing, network transmission, data transformation, storage, BIM updating, semantic interaction, and visualization. Second, the architecture is applied to representative management scenarios, including quality inspection, schedule management, safety monitoring, panoramic video surveillance, environmental sensing, risk visualization, and structural-condition assessment. Third, the proposed framework is examined through project-based validation and comparative performance indicators, while practical limitations concerning standardization, interoperability, scalability, and operation and maintenance are discussed. The purpose is not to replace established BIM or IoT systems, but to provide a coherent integration structure that links physical-site data with digital project information and thereby improves the timeliness, traceability, and interpretability of construction-management processes.

II. Research Methodology and Integration Framework

A. BIM–IoT Integration Framework

The proposed BIM–IoT integration scheme is shown in Figure 1. At the field level, the framework combines multiple sensing and data-acquisition technologies, including GPS/GIS positioning, LiDAR-based laser scanning, RFID identification, mobile data collection, environmental sensors, and status-monitoring devices. These technologies provide observations associated with materials, equipment, structural components, personnel, environmental conditions, resource utilization, and construction progress. The primary methodological requirement is that each observation be associated with sufficient temporal and spatial information to permit reliable mapping to the corresponding digital object, location, or record within the BIM-centered information environment.

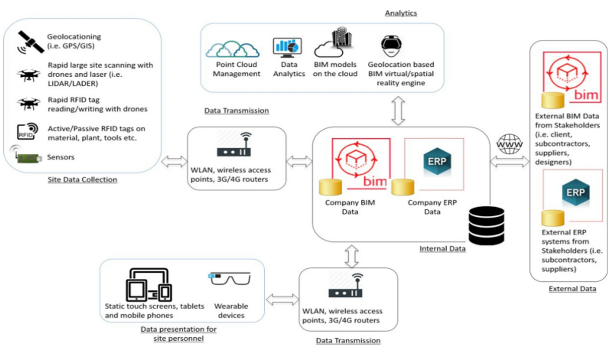

Figure 1: BIM–IoT integration scheme.

The mapping process is represented as

$$M : \{x_i, t_i, l_i\} \to D_B, \tag{1}$$

where x_i denotes an observed sensor or device value, t_i denotes the observation time, l_i denotes the observation location, and D_B denotes the corresponding BIM data-update item. Eq. (1) formalizes the association between physical observations and digital records and therefore provides the basis for synchronizing site conditions with the BIM model.

The collected information is transmitted through wireless local-area networks, wireless access points, cellular routers, and related communication nodes. The resulting data streams are directed to the enterprise data environment, where they can support BIM, enterprise resource planning (ERP), resource allocation, schedule control, cost-related analysis, and risk management. Where appropriate, information can also be exchanged with external stakeholders, including clients, designers, subcontractors, and suppliers, to support collaboration across organizational boundaries [16]. The end-to-end delay for a data item is represented by

$$T_i = T_s + T_n + T_p, \tag{2}$$

where T_s, T_n, and T_p denote acquisition, network-transmission, and processing delays, respectively. This decomposition is useful because a real-time management application can fail even when only one of these delay components becomes excessive.

The coupling between BIM and ERP states is expressed as

$$C_k(t) = f\left(B_k(t), E_k(t)\right), \tag{3}$$

where $B_k(t)$ and $E_k(t)$ represent the BIM and ERP states for management item k at time t. Consistency between internal and externally shared BIM information is constrained by

$$\left|B_k^{\text{internal}}(t) - B_k^{\text{external}}(t)\right| < \varepsilon, \tag{4}$$

where ε is the permissible consistency threshold. In practice, the interpretation of ε depends on the data type: numerical sensor variables, categorical object states, and schedule events require different consistency rules.

The enterprise data center aggregates multi-source information and supports point-cloud processing, model updating, statistical analysis, location-based visualization, and virtual or augmented visualization functions [17], [19]. Processed information can be delivered to managers through workstations, touch screens, tablets, mobile devices, and wearable interfaces, thereby closing the information loop between sensing, analysis, decision-making, and field action. To characterize visualization throughput, the framework uses the update-rate indicator

$$F_r = \frac{N_u}{T_r}, \tag{5}$$

where N_u is the number of updated nodes and T_r is the corresponding rendering time. In this study, F_r is interpreted as an update-throughput measure rather than as a conventional display-frame-rate definition; a larger value indicates that more updated model objects can be processed within a given rendering interval.

Figure 2 summarizes the principal integration paths considered in the framework. The first path operates at the database layer. A BIM model exported through a standardized format such as Industry Foundation Classes (IFC) can be decomposed into components and attributes that are stored in a database and linked to dynamic IoT records. This approach is comparatively direct and is useful where object identifiers and data schemas can be maintained consistently.

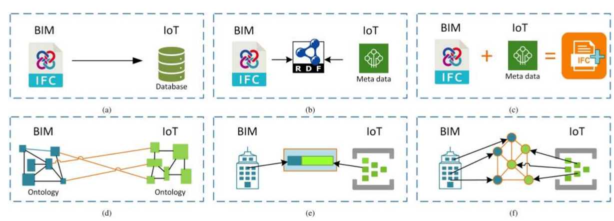

Figure 2: BIM–IoT real-time integration paths in construction projects.

The second path addresses semantic interoperability. BIM-derived IFC information can be aligned with IoT metadata through Resource Description Framework (RDF) representations or related semantic technologies. The objective is to establish shared meaning across heterogeneous data sources rather than merely transfer data fields. A simplified interoperability condition is represented as

$$F_{BIM} \cap RDF_{IoT} \neq \emptyset. \tag{6}$$

The expression indicates that a nonempty set of shared concepts, identifiers, or mapped entities is required for meaningful data exchange. More complete implementations may use ontologies, semantic rules, or standardized vocabularies to describe the mapping.

At the model-update layer, dynamic IoT metadata are associated with the corresponding BIM objects to form a time-varying, metadata-enhanced model:

$$IFC^{*}(t) = IFC_0 + Meta_{IoT}(t), \tag{7}$$

where IFC_0 is the original model and $Meta_{IoT}(t)$ denotes IoT metadata associated with time t. Although the additive notation is conceptual rather than a literal IFC operation, it emphasizes that the model state is enriched by time-dependent field observations.

Ontology alignment provides a complementary approach when BIM and IoT systems use different conceptual structures. The intended correspondence is summarized as

$$Ont_{BIM} \approx Ont_{IoT}, \tag{8}$$

where Ont_{BIM} and Ont_{IoT} denote the BIM and IoT ontological representations. The approximation symbol indicates semantic alignment rather than exact equality. Such alignment is particularly important when data are exchanged among design, construction, operation, and external information systems.

At the communication layer, middleware is used to encapsulate, parse, transform, and route data between BIM and IoT services. The conceptual mapping is written as

$$F_{IoT}(t) = M\left(F_{BIM}(t)\right), \tag{9}$$

where M is a middleware mapping function and $F_{BIM}(t)$ and $F_{IoT}(t)$ denote time-dependent BIM and IoT data flows. Middleware can reduce point-to-point coupling by centralizing transformation rules and service interfaces.

The framework also allows analytical or predictive modules to operate on combined BIM and IoT features. A generic neural-network representation is given by

$$Y(t) = NN\left(X_{BIM}(t), X_{IoT}(t)\right), \tag{10}$$

where NN denotes a trained neural-network model, $X_{BIM}(t)$ and $X_{IoT}(t)$ are BIM- and IoT-derived feature vectors, and $Y(t)$ is a predicted state, classification, or decision-support output. This analytical layer is optional; its inclusion depends on whether the management task requires prediction, anomaly recognition, or automated decision support. The broader literature demonstrates increasing interest in AI-supported and decentralized digital-construction processes, while also emphasizing the need for secure and interpretable integration [23].

Taken together, the paths in Figure 2 form a modular architecture extending from data acquisition and semantic mapping to model updating, analytics, and decision support. The framework is intentionally multi-path because construction projects differ substantially in software ecosystems, data maturity, sensor availability, and management requirements. A modular structure allows project teams to adopt only the integration mechanisms needed for a specific application while maintaining a consistent overall information architecture.

B. Data Flow and Interaction Logic

Figure 3 presents the data-flow and interaction logic used to support dynamic BIM–IoT collaboration. The architecture is organized around four functional activities: data acquisition and preprocessing, message transmission and subscription, contextual interaction, and persistent storage. The objective is to establish a bidirectional information loop in which IoT observations update the BIM-centered digital environment and BIM context, in turn, supports interpretation of incoming sensor data. This closed-loop principle is consistent with intelligent-construction management approaches that emphasize continuous state assessment and data-supported coordination [18].

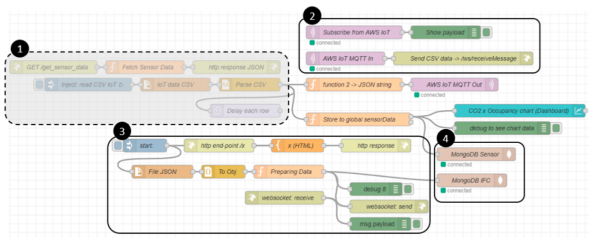

Figure 3: Data-flow and interaction-logic framework.

In the acquisition and preprocessing stage, the system receives live sensor data through an HTTP interface (for example, `GET /get_sensor_data`) or loads historical observations from CSV files for replay and testing. The parsing component standardizes field names, units, timestamps, and object identifiers before the data enter downstream services. The transformation is represented as

$$D_{IoT}(t) = Parse\left(D_{raw}(t)\right), \tag{11}$$

where $D_{raw}(t)$ is the original sensor stream and $D_{IoT}(t)$ is the standardized IoT representation. Standardization at this stage reduces ambiguity in subsequent BIM mapping and database operations.

For message transport, the framework uses a publish/subscribe mechanism based on MQTT and a cloud IoT service. Streaming observations are received through subscriptions, transformed where necessary, and republished in a structured format such as JSON for use by visualization, storage, and analysis modules. The data-flow relationship is written as

$$M_{pub}(t) = M_{sub}(t) + Transform\left(D_{IoT}(t)\right), \qquad (12)$$

where $M_{sub}(t)$ represents the subscribed message stream and $M_{pub}(t)$ represents the transformed output stream. The notation summarizes the logical transformation rather than a numerical addition operation.

The context-interaction module uses WebSocket communication to support two-way exchange between a visualization interface and the server-side BIM–IoT environment. JSON objects are parsed and associated with model context, allowing an observation to be interpreted with respect to the relevant component, space, or management state. The context relationship is represented by

$$C_{IoT}(t) = f\left(C_{BIM}(t), D_{IoT}(t)\right), \qquad (13)$$

where $C_{BIM}(t)$ denotes the current BIM context and $C_{IoT}(t)$ denotes the interpreted sensing state. The function therefore reflects the principle that the same sensor value may have different management implications depending on object type, location, schedule stage, or operational context.

Finally, the persistence layer stores time-stamped sensor and BIM-related records in a database and maintains synchronization during model updates. The consistency condition is represented as

$$|D_{BIM}(t) - D_{IoT}(t)| \leq \varepsilon, \qquad (14)$$

where ε is the allowable deviation under the adopted mapping rule. For categorical information, an equivalent logical consistency check can be used. Persistent storage is essential not only for real-time visualization but also for later reconstruction of events, quality-document traceability, claims support, and responsibility management [14], [26].

III. BIM–IoT Integration in Smart Construction Sites

A. Smart Construction-Site Implementation Process

A smart construction site can be understood as a digitally connected construction environment in which field observations, model information, management records, and decision-support functions are coordinated through an integrated information system. In the present framework, BIM provides the spatial and object-oriented information structure, whereas IoT technologies provide time-dependent observations of physical conditions. Figure 4 illustrates the quality-management workflow used to connect these two information sources. The workflow consists of three stages: 4D BIM decomposition, quality-data acquisition and mapping, and real-time quality monitoring and acceptance.

In Step I, the design BIM model is decomposed according to construction components and time-related work packages so that physical activities can be associated with model objects. A time–component mapping is expressed as

$$M_{4D}(c_i, t_j) = f_{seg}\left(BIM_{\text{as-designed}}\right), \qquad (15)$$

where c_i is the ith component, t_j is a construction time node, and f_{seg} is the model-segmentation function. The purpose of this stage is to establish a structured relationship between model components and planned construction activities. Standardized WBS-linked BIM structures can strengthen this type of object–schedule association [25].

In Step II, quality information is collected through mobile terminals and IoT-enabled devices and is associated with the corresponding BIM component. The process may include checklist data, measurements, sensor values, component status, photographs, or other structured records. The mapping relationship is represented as

$$Q_{real}(t) \xrightarrow{f_{map}} Q_{BIM}(t), \qquad (16)$$

where $Q_{real}(t)$ is the observed site-quality information and $Q_{BIM}(t)$ is the mapped BIM quality state. Automated or semi-automated mapping reduces repeated manual entry and creates a traceable association between physical inspection results and model objects.

In Step III, the mapped information is evaluated against relevant specifications or acceptance criteria, displayed in the BIM environment, and retained for subsequent traceability. The quality-status function is expressed as

$$C_{status}(t) = f_{eval}\left(Q_{BIM}(t), S_{spec}\right), \qquad (17)$$

where S_{spec} denotes the applicable specification requirement and $C_{status}(t)$ denotes the resulting quality-compliance state. This workflow is consistent with the broader objective of smart construction quality management: combining timely field data with structured model information so that nonconformities can be identified, located, communicated, and reviewed efficiently [2], [24].

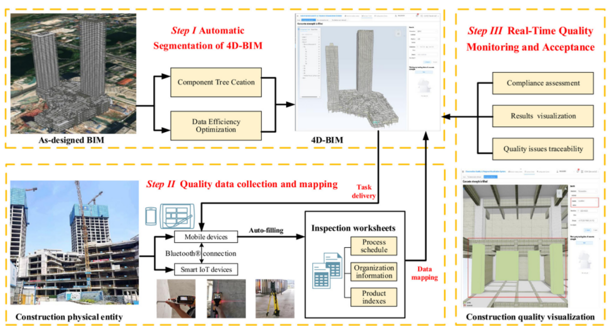

Figure 4: Smart construction-site quality-management workflow.

B. Typical Module Realization Scenarios

Safety monitoring is a principal application of the proposed framework. Figure 5 illustrates a representative sensor arrangement for structural members and the associated site-monitoring logic. Embedded or externally mounted sensors can be placed at selected beam and column locations to monitor structural or environmental conditions, while personnel- and vehicle-positioning devices provide spatial information on site movement. These observations are transmitted to the BIM–IoT environment, where they can be displayed in relation to zones, structural components, or work activities. Integrated monitoring systems that combine IoT sensing, positioning, and digital models have been shown to support construction safety and quality management [5], [6].

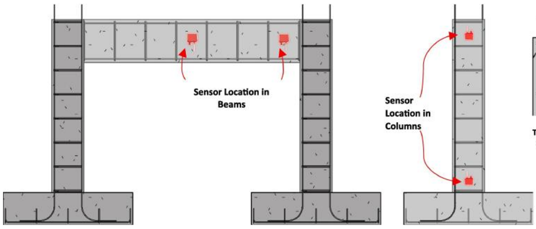

Figure 5: Layout of safety-monitoring sensors.

The relationship between positional and sensor states and a safety alarm is represented by

$$S_{alert}(t) = f_{IoT}\left(L_{person}(t), L_{vehicle}(t), L_{sensor}(t)\right), \tag{18}$$

where $S_{alert}(t)$ is the safety-alarm state at time t, $L_{person}(t)$ and $L_{vehicle}(t)$ represent the positions of personnel and vehicles, and $L_{sensor}(t)$ represents the relevant sensor state. This formulation allows safety rules to combine spatial proximity, restricted-zone logic, equipment movement, and structural-condition information.

Figure 6 illustrates how three-dimensional BIM information can support design-quality coordination and how the same model can be extended to four-dimensional schedule management. A detailed BIM model can represent the building structure, mechanical and electrical systems, pipelines, equipment, and functional spaces. Clash detection can then be used to identify spatial conflicts before field installation, reducing avoidable rework and supporting coordination across disciplines [21]. A generic clash-detection relationship is expressed as

$$C_{conflict}(i, j) = f_{detect}(E_i, E_j), \tag{19}$$

where E_i and E_j are spatial entities and $C_{conflict}(i, j)$ denotes their detected conflict state.

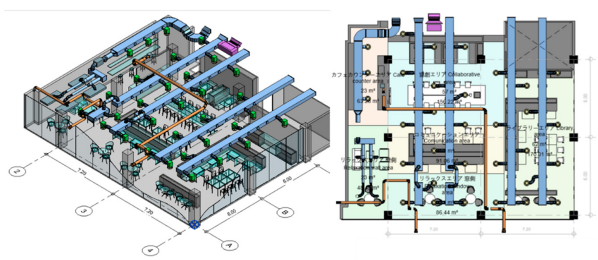

Figure 6: 3D quality management and 4D schedule optimization.

The addition of schedule information converts the 3D model into a 4D representation in which planned activities can be visualized over time. Real-time progress data can then be compared with the planned state to identify deviations and support schedule adjustment. The schedule-optimization relationship is represented as

$$S_{opt}(t) = f_{plan}\left(S_{4D}(t), R(t)\right), \tag{20}$$

where $S_{4D}(t)$ denotes the current 4D BIM schedule state, $R(t)$ denotes the resource-allocation state, and $S_{opt}(t)$ denotes the adjusted schedule plan. This logic is compatible with multilevel production planning and control approaches that integrate planning methods with project-control metrics [12].

The panoramic video and event-traceability module is illustrated in Figure 7. The 3D BIM model is used to organize inspection locations and identify components requiring attention, while inspection tasks can record object selection, sampling ratio, inspection time, inspection items, and the resulting status. A Product–Organization–Process (POP) information structure can be used to associate model objects, project organizations, and construction processes, thereby supporting the retrieval of quality records across spatial and temporal dimensions [22]. Linking BIM records with structured documentation also supports more transparent claims and responsibility-management processes [14], [26].

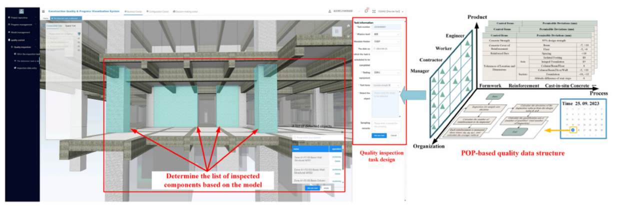

Figure 7: Panoramic video surveillance and event-traceability management.

By associating the BIM model, video records, and quality logs, the system permits managers to review both current conditions and historical events within a spatial context. The logical relationship is represented by

$$E_{trace}(t) = f_{link}\left(M_{BIM}(t), V_{CCTV}(t), Q_{log}(t)\right), \tag{21}$$

where $E_{trace}(t)$ is the reconstructed event information, $M_{BIM}(t)$ is the BIM state, $V_{CCTV}(t)$ is the video-surveillance stream or record, and $Q_{log}(t)$ is the associated inspection log. This linkage is intended to reduce the time required to locate relevant evidence and to improve the consistency of historical-event reconstruction.

IV. Experimental Design and Validation

A. Experimental Objectives

The experimental validation was designed to examine whether the proposed BIM–IoT framework could support coordinated smart construction-site management across multiple modules. The evaluation focuses on quality management, schedule management, safety monitoring, panoramic video surveillance, event traceability, environmental sensing, and visualization. The principal objectives were to assess the feasibility

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of connecting field data with BIM objects, the timeliness of data transmission and model updating, the stability of cross-module data flow, and the practical usefulness of the resulting visual and decision-support functions. The evaluation is therefore application-oriented rather than a laboratory-only test and is intended to examine how the framework operates under project conditions [23], [24].

B. Experimental Environment and Data Sources

The validation was conducted on a large commercial-complex project under construction. The field hardware included mobile terminals, IoT sensors, high-definition cameras, personnel-positioning equipment, and network communication devices. The software environment included Revit, Navisworks, AWS IoT Core, MongoDB, Node-RED, and project-specific integration functions. BIM information originated from project design files and was transformed through IFC4 and JSON-based representations for subsequent processing [25]. IoT observations were obtained from field sensors, positioning devices, and video streams. The experimental collection period was 30 days, with the principal sensor stream sampled once per minute, producing a large spatiotemporal dataset for integration and visualization.

In addition to sensor and model data, the study includes descriptive implementation-factor assessments presented later in Figures 11 and 12. These assessments summarize professional judgments concerning BIM- and ERP-related implementation factors. Because these ratings are used as supplementary descriptive evidence, they are interpreted in conjunction with the technical validation rather than as a substitute for direct system-performance measurements.

C. Experimental Procedures and Protocols

The experimental scenario and principal implementation steps are summarized in Figure 8. The procedure began with conversion of the design BIM information into a component structure suitable for association with site observations. Smart sensors and mobile inspection devices were then deployed according to the component and spatial layout. Quality-related observations, including concrete-related measurements and reinforcement-inspection information, were recorded through mobile and IoT interfaces and transmitted by Bluetooth or wireless networking to the back-end environment. Task information was stored in a structured database and associated with BIM objects so that corresponding components could be highlighted and their status updated in the 3D scene. POP-oriented information organization was used to maintain relationships among products, organizations, processes, and quality records [26].

For schedule management, construction activities were linked with the BIM model to form a 4D representation. IoT-derived progress information was compared with planned progress, allowing the system to identify deviations and provide schedule-adjustment information. For safety management, positioning devices and field sensors were used to monitor personnel, vehicles, and selected structural states. The communication workflow was evaluated through message publication and subscription, database updates, and WebSocket-based real-time data push. These procedures were intended to test not only individual functions but also the continuity of data movement from the physical construction site to the integrated digital environment.

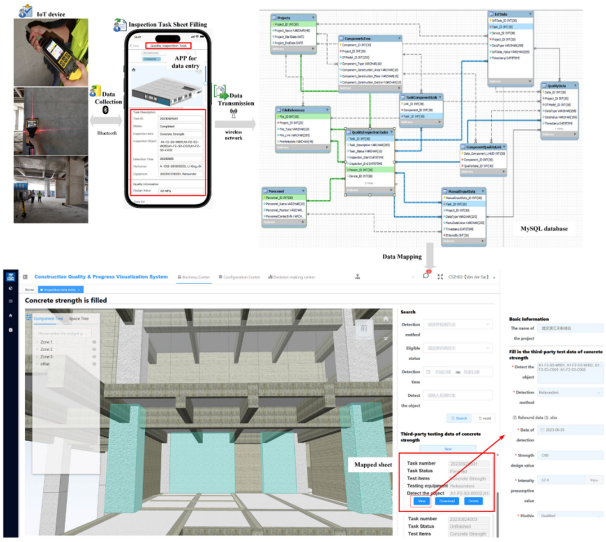

Figure 8: Experimental scenario and implementation procedure.

D. Experimental Results and Analysis

Table 1 summarizes the comparative performance of the principal management modules.

Table 1: Evaluation results for typical modules in the BIM–IoT integrated solution.

Module	Evaluation Metric	Traditional Method Level	BIM–IoT Solution Level	Improvement
Quality Management	Task Generation Time for Inspection	15 min	8 min	↓46.7%
	Accuracy of Issue Detection	89.0%	98.2%	↑10.3%
	Timeliness of Data Entry After Backfilling	T+1 day	Real-time	Significantly Improved
Schedule Management	Schedule Deviation Control Range	±3 days	±1 day	Reduced by ∼ 66%
	Time to Detect Issues in Advance	T+2 days	T+1 day	50% earlier
Safety Management	Response Time for Abnormal Event Alarms	15–20 s	3 s	↓80%
	Alarm Accuracy Rate	93.5%	99.2%	↑6.1%
Video Traceability	Time for Event Retrieval	10–15 min	2–3 min	↓75%
	Traceability Accuracy	95.0%	99.0%	↑4%

The values indicate that the BIM–IoT solution reduced inspection-task generation time from 15 to 8 minutes, increased issue-detection accuracy from 89.0% to 98.2%, and changed quality-data entry from a next-day process to a real-time process. In schedule management, the reported deviation-control range improved from approximately ±3 days to ±1 day, while issue-detection time improved from approximately two days to one day. In the safety module, abnormal-event alarm response decreased from 15–20 seconds to approximately 3 seconds, with reported alarm accuracy increasing from 93.5% to 99.2%. Video-based event retrieval decreased from 10–15 minutes to 2–3 minutes, and traceability accuracy increased from 95.0% to 99.0%. These results support the practical value of integrating field observations with spatial and temporal BIM information, although the reported comparisons should be interpreted within the scope of the project and procedures evaluated.

Figure 9 presents the concrete-quality monitoring results. IoT sensors embedded in concrete test blocks and cast-in-place columns were used to collect temperature-related information and support strength-development monitoring. The test blocks were cured under controlled conditions, whereas the columns were exposed to natural site conditions, allowing the monitoring system to represent different curing environments. Figure 9(c) shows that the sensing arrangement distinguished temperature differences associated with the two environments. Figure 9(d) presents the development of equivalent age over time, and Figure 9(e) compares strength-development trends for the investigated concrete proportions under the corresponding temperature–time conditions. These observations are consistent with the practical objective of remote, real-time concrete monitoring using BIM–IoT integration [27].

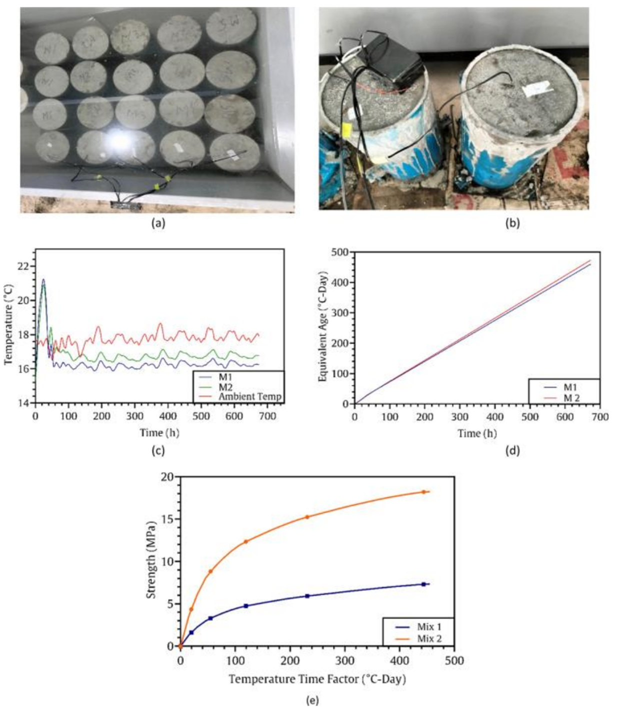

Figure 9: Experimental results of concrete quality monitoring.

Figure 10 illustrates environmental monitoring and spatial-modeling results. IoT sensors were used to collect environmental parameters such as CO_2 concentration, occupancy-related counts, temperature, and humidity. The reported correlation matrix shows a positive correlation between CO_2 concentration and the number of people ($r = 0.30$) and a positive correlation between temperature and humidity ($r = 0.33$). These values indicate measurable but not necessarily strong linear relationships, and they demonstrate how multi-parameter monitoring can be summarized within the management platform. The spatial-modeling interface links environmental observations with BIM-defined spaces and their associated attributes, enabling managers to interpret environmental data in relation to specific rooms or zones rather than as isolated sensor records.

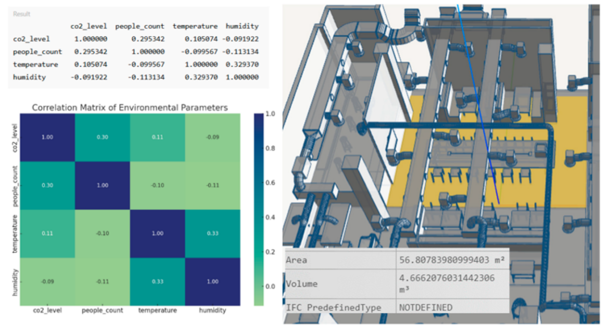

Figure 10: Environmental monitoring and spatial-modeling results.

Figure 11 summarizes the reported importance ratings for factors influencing BIM-centered implementation within the integrated framework. Factors such as BIM software type and cost, BIM functionality, parameterization of BIM elements, and interoperability with other database tools received comparatively high ratings. Parameterization is particularly important because model elements must contain stable identifiers and attributes if they are to be connected reliably with IoT observations, schedules, inspection records, and database entries. Ease of navigation, level of detail, implementation time, and software characteristics also affect adoption because a technically capable system may still perform poorly in practice if project teams cannot maintain or use it efficiently. These findings are compatible with broader research identifying system integration and management alignment as central issues in intelligent construction [22], [24].

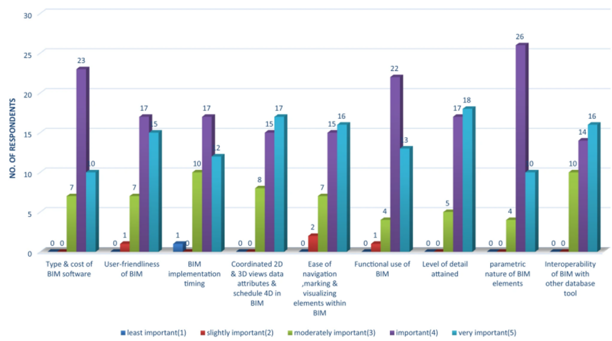

Figure 11: Importance assessment of factors influencing BIM–IoT framework implementation.

Figure 12 presents the corresponding assessment of ERP-related implementation factors. ERP module functionality received a high proportion of “very important” responses, while interoperability between ERP systems and other database tools and the ability to aggregate heterogeneous project information were also rated highly. Security and module reliability were prominent concerns, reflecting the importance of dependable data exchange when BIM, IoT, and enterprise information are combined. Software type and cost, implementation time, scalability, and ease of development received somewhat lower "very important" ratings but remained relevant to implementation. The results reinforce the need to treat BIM–IoT deployment as an enterprise-information problem rather than as a stand-alone visualization task [11].

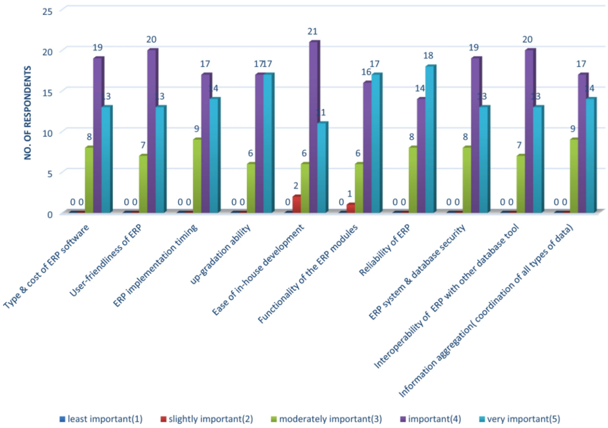

Figure 12: Importance assessment of factors affecting ERP-system implementation.

Figure 13 demonstrates the construction-site risk heat-map function. Environmental, personnel, and spatial information are associated with the 3D BIM environment and summarized using a color-gradient representation. Areas displayed in red correspond to higher potential-risk levels, while yellow and blue indicate progressively lower values according to the adopted visualization rule. The associated tabular information records attributes such as element number, name, and potential value. This coordinated spatial and tabular representation allows a manager to move from a high-level risk overview to the underlying component or zone information without leaving the integrated environment.

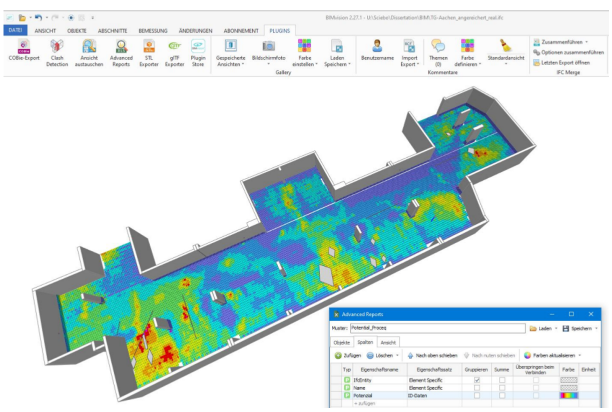

Figure 13: Construction-site risk heat map and data-analysis results.

Figure 14 shows the structural-safety visualization module. Stress- and displacement-related observations collected through IoT sensing are superimposed on the BIM structural model to generate a color-coded representation of component condition and safety margin. In the visualization, red identifies components requiring greater attention, whereas blue and green represent more favorable states under the adopted assessment rule. By linking condition data with spatially explicit model objects, the system allows managers to identify the location of potentially critical components and to interpret measurements in relation to the surrounding structural configuration. This type of BIM-enabled real-time structural monitoring is consistent with recent digital-twin research in structural health assessment [6].

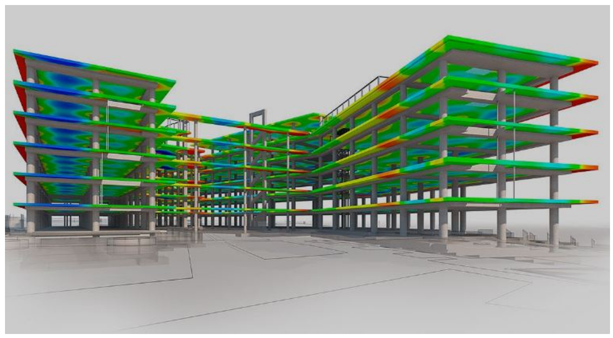

Figure 14: Visualization results for structural safety performance.

Figure 15 presents multidimensional modeling and simulation for high-rise construction. Figure 15(a) illustrates parametric modeling associated with construction-wall conditions and tower-crane arrangement. Figure 15(b) presents the visual organization of the overall construction plan, including temporary structures and scaffolding. Figure 15(c) shows refined modeling and force-related simulation of selected components, while Figure 15(d) presents scaffolding-system layout and detail visualization. Figure 15(e) focuses on parametric representation of complex connection details, and Figure 15(f) compares a BIM-based construction-node arrangement with the corresponding site condition. Collectively, these views demonstrate how model detail, temporary-work planning, spatial coordination, and site comparison can be combined within a common digital environment to support construction planning and safety management [16], [17].

Figure 16 compares the BIM-based project simulation with the corresponding construction-site condition. The model presents the principal architectural form, spatial layout, floor progression, and podium relationship of the high-rise complex, while the site image provides a physical reference for the observed stage of construction. The visual correspondence between the model and the site demonstrates the practical value of model-based progress communication and provides a basis for identifying deviations when the digital representation and field state no longer agree. Such comparison is particularly useful when 4D BIM is integrated with current field observations, because schedule information can then be evaluated in a spatially explicit manner rather than through tabular progress reports alone.

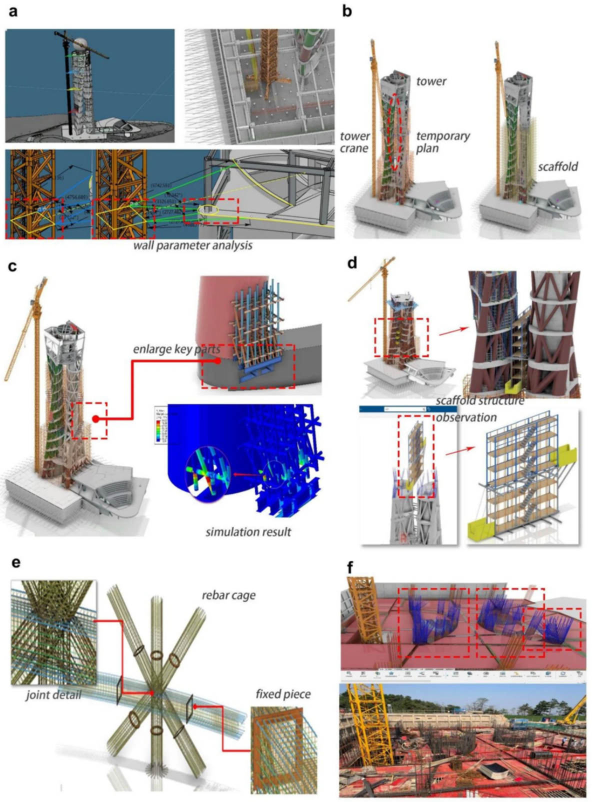

Figure 15: Multidimensional modeling and simulation results for high-rise construction.

Figure 16: Comparison between the construction simulation model and the actual site condition.

V. Discussion

The validation results indicate that the practical value of BIM–IoT integration arises primarily from the continuity of information between the physical construction site and the digital management environment. BIM and IoT address different but complementary information requirements. BIM provides object identity, geometry, location, relationships, planned sequence, and management context, whereas IoT devices provide time-dependent observations of the physical state. When these two information sources are used separately, BIM may become outdated and sensor data may remain difficult to interpret spatially. Their integration creates an information chain in which an observation can be connected to a component, a space, a work activity, a responsible management process, and a specific time. This relationship explains why the proposed framework can support several management modules without requiring a completely independent information architecture for each application.

The quality-management results are particularly illustrative. Under conventional inspection procedures, task generation, field recording, subsequent data entry, and issue localization may occur as separate activities. In the integrated workflow, inspection information is linked directly to model components, which reduces repeated identification and provides a structured location for storing and retrieving the resulting records. The decrease in inspection-task generation time and the increase in issue-detection accuracy reported in Table 1 are therefore consistent with the underlying information architecture rather than being attributable to visualization alone. Wang et al. similarly demonstrated the value of linking real-time quality data with 4D BIM for monitoring and acceptance [2], while the BIM platform developed by Kim et al. shows how standardized work-breakdown structures can strengthen the association between model objects and management information [25]. The present study extends this principle by connecting inspection data with a wider set of site-management functions.

The concrete-monitoring example provides a second illustration of the difference between simple sensing and integrated sensing. A temperature sensor can provide technically valid measurements without BIM, but the management value increases when the observation is associated with the relevant concrete element, curing condition, construction time, and quality record. The monitoring results shown in Figure 9 demonstrate how temperature-related observations and strength-development information can be interpreted in a component-oriented construction context. This is closely related to the remote concrete compressive-strength monitoring framework reported by Iqbal et al. [27]. From a management perspective, the important point is not merely that a sensor can transmit data, but that the transmitted data can be linked with a digital object and retained in a form that supports later review, acceptance, or traceability.

The schedule-management results show a similar pattern. Four-dimensional BIM establishes the planned temporal relationship among work packages and model elements, while IoT-derived observations provide evidence of actual progress. The comparison between these information sources permits deviations to be expressed in relation to both time and physical location. The reported reduction in the schedule-deviation control range therefore reflects the ability to identify differences between planned and observed states earlier in the management cycle. This approach is compatible with integrated production-planning research that emphasizes the need to connect planning methods, control metrics, and project information across different management levels [12]. It is also consistent with digital project-management frameworks that use BIM to improve information coordination throughout prefabricated and transnational project processes [21]. In practice, however, schedule optimization still depends on the quality of the underlying work-breakdown structure, the reliability of progress observations, and the accuracy with which field events are mapped to BIM objects.

Safety management benefits from the same integration principle but introduces additional requirements concerning response time and reliability. The reported reduction in alarm-response time to approximately three seconds indicates that the combined sensing and communication architecture can support near-real-time event handling under the evaluated conditions. Figure 5 shows the role of distributed sensor placement, while Figure 14 demonstrates how structural-condition information can be visualized within the BIM environment. The intelligent BIM-enabled digital-twin framework proposed by Hu et al. likewise emphasizes real-time structural health monitoring through wireless IoT sensing and structural analysis [6]. The integrated smart construction monitoring system of Kim et al. combines point-cloud information, IoT sensing, and positioning technologies for safety and quality applications [5]. These studies support the broader conclusion that safety applications require not only data collection but also reliable contextualization and communication. A rapid alarm is useful only when the system can identify the relevant location, object, event type, and management response.

The environmental-monitoring results in Figure 10 further demonstrate the importance of contextual interpretation. Sensor correlations by themselves provide limited management information, especially when the magnitude of the relationship is modest. By linking environmental observations with BIM-defined spaces, the framework allows managers to determine where a measurement was obtained, which activities or occupants were associated with the location, and whether the observed condition is persistent or temporary. This capability is consistent with BIM–IoT research in facility management and sustainable building operation, where the integration of sensor data and spatial information is used to support water, energy, and environmental management [9], [15]. The present construction-stage application shows that similar principles can be used before the operational phase of a building.

The event-traceability and document-management functions also have implications beyond immediate site supervision. Construction projects generate large quantities of inspection records, photographs, video, model revisions, instructions, and other documents. If these records are maintained in disconnected systems, later reconstruction of an event may require extensive manual searching. Figure 7 demonstrates a model-centered approach in which video and quality records are linked with time and location. The reduction in event-retrieval time reported in Table 1 is consistent with this design objective. Related BIM-based document-management research has shown that structured digital records can improve retrieval and support construction-claim management [14]. Blockchain-based responsibility-management frameworks have also been proposed to strengthen traceability and accountability for BIM information [26]. Although blockchain is not required by the present framework, these studies highlight the broader importance of persistent, auditable relationships among project objects, records, organizations, and decisions.

The implementation-factor assessments shown in Figures 11 and 12 indicate that successful integration depends on more than technical data transmission. Model parameterization, software functionality, database interoperability, information aggregation, reliability, and security were all identified as important considerations. This finding agrees with research showing that IoT adoption in smart buildings and infrastructure is constrained by technical, standardization, complexity, economic, and organizational barriers [11]. It also aligns with recent analyses of intelligent construction in which system integration, multi-field collaboration, and compatibility between technical requirements and management processes remain major challenges [22]. Consequently, a technically correct BIM–IoT interface does not guarantee successful project adoption. The integrated system must also fit existing workflows, responsibilities, data standards, and user capabilities.

Interoperability remains one of the most important technical issues. The present framework uses IFC, JSON, RDF-oriented semantic concepts, MQTT, WebSocket communication, and database mapping as representative mechanisms. These technologies address different layers of interoperability. IFC provides a standardized building-information representation; JSON supports lightweight data exchange; semantic representations can align concepts across domains; MQTT provides an efficient publish/subscribe mechanism for sensor streams; and WebSocket communication supports continuous interaction with user interfaces. Earlier reviews of BIM and IoT integration similarly identified multiple integration patterns rather than a single universal solution [10]. This observation supports the multi-path design adopted in Figure 2. Different projects may require different combinations of direct database linkage, middleware, semantic alignment, cloud services, or model enrichment.

A further issue is the relationship between data timeliness and data quality. Faster transmission is not automatically beneficial if sensor records are incomplete, incorrectly mapped, duplicated, or inconsistent with the model. Eqs. (2) and (14) therefore represent two complementary requirements: the system should minimize end-to-end delay while maintaining acceptable consistency between physical observations and digital records. In practice, data-quality controls should include time synchronization, identifier validation, range checking, missing-value handling, and verification of object mappings. As the number of devices and model objects increases, these tasks become increasingly important because even a small error rate can generate a large number of incorrect updates.

Scalability is similarly important. The project validation demonstrates feasibility under the reported 30-day monitoring period, but larger deployments may involve substantially more devices, higher-frequency streams, multiple buildings, and many concurrent users. The modular architecture proposed in this study is intended to support such expansion, yet additional work is required to evaluate message throughput, storage growth, visualization performance, and fault tolerance at larger scales. Cloud-based and distributed approaches can improve scalability, but they also introduce additional concerns regarding cybersecurity, access control, and data governance. Recent research on decentralized artificial intelligence and digital-twin governance illustrates the growing importance of secure data and model management in construction information systems [20], [23].

The results should also be interpreted with respect to the scope of the validation. The reported improvements were obtained within a specific commercial-complex project and under the particular software, sensing, communication, and management procedures used in the study. They therefore demonstrate project-level feasibility and comparative performance rather than universal effect sizes applicable to every construction environment. Site layout, network quality, sensor selection, model detail, workforce practices, and organizational maturity can all affect the achievable benefits. For this reason, the principal contribution of the study lies in the integrated architecture and demonstrated workflow rather than in treating the numerical improvements as fixed benchmarks for all projects.

From a construction-management perspective, the framework also illustrates a transition from document-centered management toward state-centered management. Traditional project records frequently describe what happened after an inspection, meeting, or reporting cycle. By contrast, a BIM–IoT environment can maintain a continuously updated representation of selected project states. This does not eliminate the need for human judgment; rather, it changes the information available to managers when judgments are made. Visualized spatial context, time-stamped sensor information, schedule status, and linked records can reduce the effort required to assemble evidence and may help managers focus attention on deviations that require intervention.

Overall, the project results and the supporting literature suggest that BIM–IoT integration is most effective when it is treated as an information-management architecture rather than as the simple connection of a model to sensors. The architecture must specify how data are identified, transmitted, transformed, stored, contextualized, visualized, evaluated, and retained. It must also define how the resulting information supports actual quality, schedule, safety, and traceability decisions. The framework proposed in this paper addresses these requirements at a practical level and provides a basis for future extensions involving more advanced analytics, digital twins, automated decision rules, and interoperable lifecycle information environments.

VI. Conclusions

This study proposed and validated a BIM–IoT integrated framework for smart construction-site management in response to the growing need for timely, traceable, and data-supported management under construction-industry digital transformation. The framework connects sensing, communication, data transformation, storage, semantic association, BIM updating, visualization, and management feedback within a unified architecture. In this way, field information concerning environmental conditions, personnel, equipment, construction components, quality status, progress, and safety can be linked to corresponding digital objects and management records rather than remaining in isolated systems.

Project-based validation was conducted across quality management, schedule management, safety monitoring, event traceability, environmental sensing, and structural visualization. The comparative results reported in Table 1 indicate improvements in inspection-task generation time, issue-detection accuracy, schedule-deviation control, abnormal-event alarm response, and historical-event retrieval. Figures 9–16 further demonstrate the use of the integrated environment for concrete monitoring, environmental analysis, implementation-factor assessment, risk mapping, structural-safety visualization, multidimensional construction simulation, and comparison between digital models and actual site conditions. These results support the practical argument that BIM becomes more useful for construction management when its structured spatial information is continuously connected with field data rather than updated only through periodic manual processes.

The study also identifies limitations that remain important for future deployment. BIM and IoT systems continue to differ in data structure, semantics, identifiers, communication protocols, and update frequencies. Large projects may also face scalability problems as the number of sensors, model objects, users, and external systems increases. Furthermore, implementation requires sustained maintenance of device networks, databases, middleware, data mappings, and model quality. Future work should therefore focus on more standardized interfaces, robust semantic mapping, automated data-quality control, scalable message processing, cybersecurity, lifecycle-oriented governance, and evaluation across multiple project types. Additional validation with larger and more diverse project samples would also strengthen the generalizability of the performance observations reported here. Within these limitations, the proposed framework provides a structured and extensible basis for integrating BIM and IoT technologies in smart construction-site management.

Data Availability

The data reported in this study are summarized in the figures and table included in the article.

Conflicts of Interest

The author declares that there are no conflicts of interest related to this work.

Funding Statement

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