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Designing a BIM-enhanced digital twin architecture for construction pollution management in building renovation projects

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ABSTRACT

Pollution created by building renovation activities poses a hazard to human health and the proximate environment. Integrating building information modelling (BIM) with digital twin (DT) technology offers a promising means for real-time monitoring and enabling collaboration among project participants. However, it is challenging to transform the BIM models of a renovated facility into a DT platform for monitoring and reporting construction pollution on-site. This paper proposes a BIM-enhanced DT architecture for managing construction pollution in building renovation projects. The platform entails five key components: physical entity (PE), virtual model (VM), DT data (DD), services (Ss), and connections (CNS). To resolve ambiguities in information requirements, a novel Level of Information Need (LOIN) framework for BIM-enhanced DT was established. The interplay among LOIN, Level of Development (LOD), and DT functionalities defines the minimum information needed in the information containers and the metadata structure required for pollution hotspots, compliance assessment, and automated analytics. To illustrate its efficacy and practicality, the DT architecture was applied to an auditorium renovation project, where static BIM data were integrated with dynamic pollution parameters captured by IoT sensors and managed in a Common Data Environment (CDE). The results showed its capability to systematically and efficiently acquire, integrate, treat, and analyze important data.

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Building information modelling (BIM); digital platform; IoT sensors; Level of Development (LOD); Level of Information Need (LOIN); real-time monitoring

Introduction

Modern construction projects always face numerous challenges, especially resource depletion and escalating construction costs, which prompt all stakeholders to adopt various sustainability concepts, such as circular economy (Haruna et al. 2024). Building renovation promotes circular design by extending the structural lifespan of a building and minimizing resource consumption. However, pollution created by building renovation activities often poses a hazard to human health and the proximate environment. Among the pollutants, particulate matter (PM) is widely recognized as the most critical (Yan et al. 2023), alongside gaseous contaminants (Nazif et al. 2025), volatile organic compounds (VOCs), and harmful chemicals (Ismaeel et al. 2023). Elevated noise levels disrupt patient recovery and building occupants, and increase occupant stress (Zou et al. 2020), while machinery vibrations may compromise structural integrity, producing wall fissures and damaging electrical and plumbing systems (Longinow and Mohammadi 2022; Choi et al. 2023). Collectively, these impacts contribute to unacceptable indoor environmental quality (IEQ) concerns.

Environmental laws of many countries regulate the installation of pollution monitoring systems on construction sites to detect and report pollutant exposure for building occupants and surrounding communities. Yet traditional environmental measures like proper ventilation, gap sealing, and noise barriers cannot adequately control the impact of construction pollution. This is primarily attributed to non-systematic, fragmented data and inefficient information management (Doukari et al. 2024; Ghanbari

et al. 2024) and data processing (Daniotti, Masera, et al. 2022) among project stakeholders. The reliance on paper-based documentation further increases the likelihood of errors, omissions, and inconsistencies (Wang M et al. 2024). The absence of a common repository and data results in poor energy efficiency, management, and IEQ (Salvalai et al. 2026). This leads to data loss during project execution. Furthermore, assigning responsibilities for design, construction, and facility management (FM) to different parties often causes information fragmentation (Bjørnskov and Jradi 2023), hindering project owners' ability to maintain operational continuity and make informed decisions (Sacks et al. 2018). Traditional hierarchical stakeholder relationship structures cause decision-making bottlenecks, leading to delays and poor decision-making (Pan and Zhang 2021).

Building information modelling (BIM) has emerged as a pivotal enabler to mitigate these issues by enhancing direct stakeholder communication and empowering workers to make informed decisions (Wijeratne et al. 2024). When strategically integrated and combined with real-time data streams from Internet of Things (IoT) devices, organized and managed within a Common Data Environment (CDE), the BIM model evolves into a foundation for a BIM-enhanced Digital Twin (DT) platform that promotes dynamic, bidirectional interaction between physical and virtual systems (Revolti et al. 2024).

Despite its potential, establishing a BIM-enhanced DT for pollution management in building renovation projects remains technically challenging due to fragmented building data, heterogeneous information sources, and complex synchronization requirements (Eneyew et al. 2022; Pauwels et al. 2024). It requires a rigorous alignment with international standards (e.g. ISO 19650), accurate calibration and deployment of IoT sensors, consistent data structures for real-time exchange, and seamless interoperability across heterogeneous digital platforms (Madubuike et al. 2022). The synchronization of dynamic sensor data with BIM-enhanced semantic databases introduces substantial complexity in ensuring model fidelity, data granularity, and contextual interpretation (Oliveira et al. 2024).

Moreover, information management in the CDE remains persistent challenges such as information overload and insufficient data curation in the CDE (Du et al. 2020), which are exacerbated when project owners or facility managers fail to identify and manage their specific information needs (Werbrouck et al. 2019). To achieve this, project owners must carefully identify relevant BIM data aligned with their objectives by establishing clear information requirements for data production and storage, ensuring an efficient information flow (Oliveira et al. 2024). Exchange information requirements (EIR), under ISO 19650, outlines necessary information, timing, and format for the information delivery among the parties; clarifies stakeholders' roles; minimizes ambiguity, and standardizes data exchange protocols (Montoya and Roberto 2022). These are supported by the Level of Information Need (LOIN) and the Level of Development (LOD) framework defined in the BIM Execution Plan (BEP), which ensure consistent geometric and semantic information delivery aligns closely with the pre-defined metadata structures necessary for DT development (Brumana et al. 2022).

Because advanced DT applications require highly specific alphanumeric data and documentation rather than just detailed 3D geometry, a systematic strategy LOIN concept enables project teams to define the precise information requirements for the DT without over-modelling the geometry (El Sibai et al. 2025). Nevertheless, there is still a lack of formally defined BIM modelling and metadata structures in the CDE's information containers that enable the systematic integration of static BIM datasets with real-time IoT data for DT applications in building renovation projects. The conceptual framework for LOIN, which directly defines virtual models of a BIM-enhanced DT remains underexplored.

To fill this research gap, we propose a BIM-enhanced DT architecture tailored for managing construction pollution during building renovation projects. Defining the LOIN is the first and essential step toward developing a fit-for-purpose BIM model for a BIM-enhanced DT. The proposed architecture identifies essential information required for structuring BIM models that can process both static and dynamic data. We explore the relationships among the five dimensions in the CDE of a BIM-enhanced DT framework in building renovation. To support the analysis, we conducted a comprehensive literature review and semi-structured interviews to examine the evolution from conventional construction practices to BIM-enhanced DT systems.

These findings helped us delineate the architecture of the BIM-enhanced DT and the LOIN framework, which were subsequently implemented in an auditorium renovation project as a proof of concept.

The results showed improved semantic consistency and traceability for pollution monitoring, enabling a bidirectional data exchange and regulatory compliance tracking. The LOIN provides stakeholders with an understanding of information flow and collaboration workflow for pollution monitoring and management during renovation. This approach equips asset owners and contractors with actionable insights to implement BIM-enhanced DT solutions, which can safeguard neighbouring communities, mitigate health risks, and improve safety for construction workers during building renovation.

Background

BIM-enhanced DT in construction pollution monitoring

Low-cost sensor networks (LCSNs) and low-cost IoT sensors (LCSs) were increasingly prominent in environmental sciences for their capacity to produce extensive real-time monitoring data (Silva et al. 2026). However, conventional dashboard solutions often cannot represent spatial relationships or pinpoint the exact locations of monitored hotspots. Operating independently from advanced CDEs and construction workflows, these systems offered limited spatial context and data integration (Zhou and El-Gohary 2021; Nadeem et al. 2023). Although the integration of IoT and geographic information systems (GIS) significantly enhanced construction monitoring through real-time location tracking and spatial visualization (Liu et al. 2025; Valinejadshoubi et al. 2025), these technologies often operated in silos and lacked seamless integration with construction-specific digital ecosystems.

Recent studies have advanced IoT-BIM integration for real-time data acquisition on construction sites and automated systems for data transmission and storage through interactive DT platforms (Boltsi et al. 2025; Valinejadshoubi et al. 2025). Modular IEQ sensing approaches have also been developed, including DT-based KPI-driven smart building platforms (Piras et al. 2025), IoT-ML-BIM-integrated DT frameworks for indoor air quality (IAQ) monitoring (Qian et al. 2024), and HBIM-XR-enabled DT platform for IEQ analysis in heritage building (Banfi et al. 2025). Despite these advances in sensing infrastructures and digital monitoring concepts, methodologies for aligning these platforms with regulatory frameworks and BIM systems remain underdeveloped.

Managing environmental pollution in renovation sites calls for a cost-effective, portable, and easily deployable solution, which can adapt to changing spatial arrangements and unpredictable pollution sources (Francisco et al. 2020). Most current research on BIM and DT enablers focused on new construction projects (Lu et al. 2020; Qian et al. 2024). Other studies relied on proprietary hardware and complex deployment processes (Seabra et al. 2021; Hong et al. 2022), which were impractical for the transient nature of renovation projects.

A DT for construction was defined through the harmonious integration of static data from BIM models and dynamic data from cognitive technologies into a CDE (Sacks et al. 2020). While defining LOIN facilitates this physical-to-digital data exchange (Liu et al. 2021; Godager et al. 2022), excessive information requirements can burden project management. Despite prior studies having examined scan-to-BIM processes and defined BIM information requirements for specific use cases (Banfi et al. 2022; Nguyen et al. 2023), limited research has explicitly specified how such BIM models should be structured for DT implementation in the CDE. Although previous studies clarified the flows of static and dynamic information within CDE solutions and linked them to stakeholders' roles in the CDE workflow (Pham et al. 2025), a systematic process for developing and managing different information categories in the architectural framework remains missing. From this perspective, the value of a clearly structured BIM-enhanced DT architecture supported by well-defined LOIN specifications is evident. Such an approach ensures the consistent integration of BIM, IoT, and CDE workflows, while improving alignment between project services and stakeholder needs.

From non-BIM to BIM ecosystems

BIM offers a structured data environment that ensures consistency between graphical and non-graphical information throughout the project life cycle, thereby reducing information fragmentation and mitigating data exchange inefficiencies (BSI 2020; Ali et al. 2021). Its interoperability is enabled

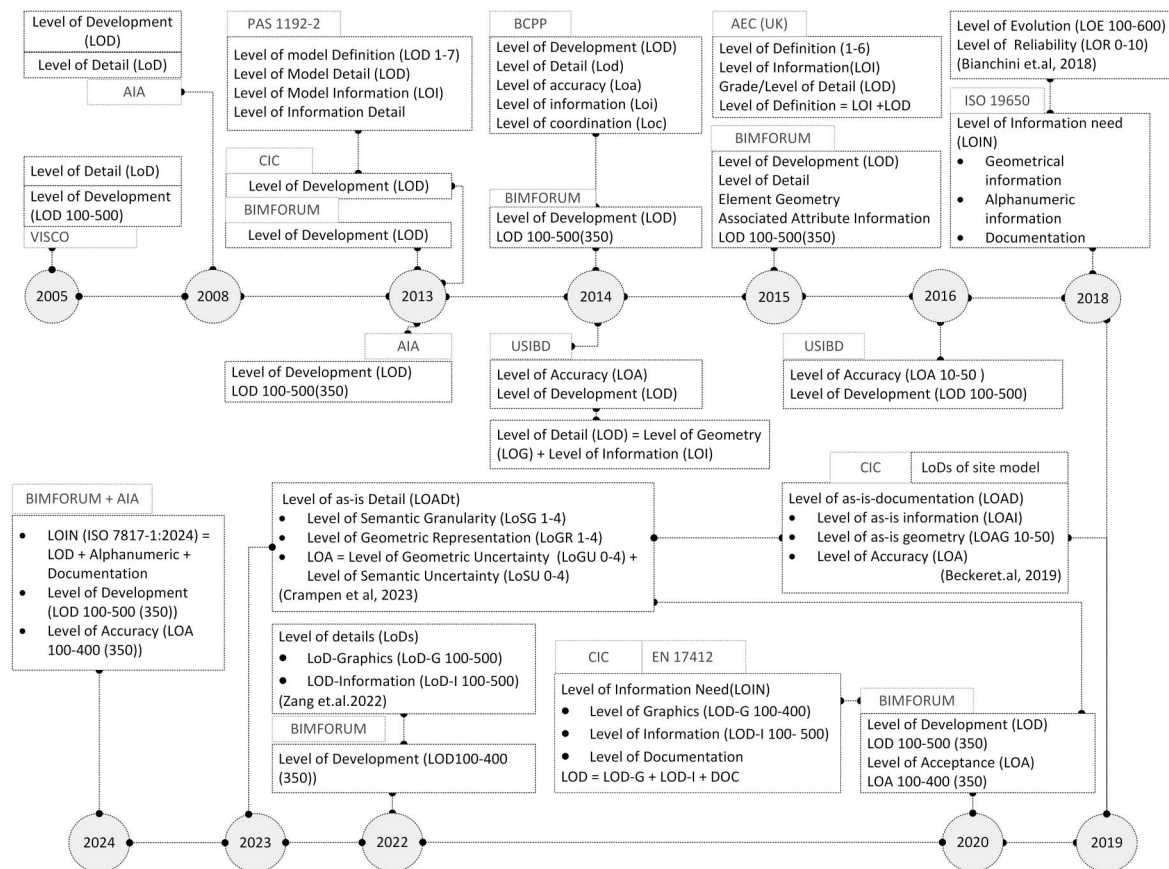


Figure 1. Evolution of the level of X in BIM model development.

through standardized formats such as Industry Foundation Classes (IFC) and Construction-Operations Building Information Exchange (COBie) (NBIMS-US 2015; ISO 2024). Harnessing the digital methodology made it possible to optimize and avoid problems related to large-scale works and construction sites located in central residential areas (Muzy et al. 2023).

BIM progression is governed by hierarchical standards, enabling the structured information delivery through standardized model evolution pathways, as illustrated in Figure 1. The term ‘level of X’ is a generic way to represent BIM progression (Succar and Poirier 2020). This term collectively refers to various specifications that define geometric representation (Level of Detail), modelling maturity (Level of Development), fidelity of the as-built representation (Level of Accuracy and Level of Reliability), semantic richness, and data granularity (Level of Information and Level of Information Need).

Digitalizing renovation projects using BIM usually follows the integration of pre-existing BIM archives or the digitization of undocumented ‘as-is’ conditions. In cases where legacy BIM data is available, project information is typically organized and adhered to a framework such as the UK’s Level of Definition (LoD), which disaggregates graphical representation from semantic attributes (i.e. Level of Information, LoI) (BSI 2012, 2018b). These frameworks have evolved to support extended FM functionalities and operational workflows through refined LOD hierarchies (Salzano, Miano, et al. 2023).

Existing LoD and LoI frameworks frequently fall short of addressing task-specific or phase-dependent information requirements. To bridge this gap, the British Standards Institution (BSI) introduced the LOIN, which is a purpose-driven methodology for defining project-specific information contents based on stakeholder roles, life-cycle phases, and intended uses (BSI 2020). The LOIN (formally defined in ISO 7817-1, which replaced EN 17412) advances interoperability by embedding contextual metadata protocols and clarifying exchange requirements, thereby strengthening traceability and inter-organizational coordination (BIMForum 2024; ISO 2024).

In projects lacking digital data, BIM initiation begins with the acquisition of spatial and semantic data through survey-grade protocols. The fidelity in such workflows is governed by classification

systems such as the Level of Accuracy (LOA), the Level of As-Is Development (LOAD), and the Level of Evolution (LOE) (USIBD 2019; Crampen and Blankenbach 2023). In heritage contexts, additional specifications such as Historical BIM (H-BIM), the Level of Reliability (LOR), and the Level of Semantic Granularity (LoSG) have been adopted to ensure model trustworthiness, especially where historical accuracy is paramount (Bianchini and Nicastro 2018). Grades of Generation (GOGs) are applied to clarify the modelling methodology and degree of automation involved in deriving BIM elements from point cloud data (Banfi et al. 2022).

States of BIM models across the building life cycle

The amount of information contained in the BIM model classified under the *level of X* is directly related to the definition of BIM states throughout the project life cycle. As BIM model states are digital expressions that evolve to support specific decision-making phases (Tuhaise et al. 2023), the level of X acts as the mandatory data baseline for each state; it ensures that the model possesses the requisite detail to support the analytical functionalities of a DT at any given stage. Figure 2 illustrates the six main states of BIM models along a facility's life cycle, namely, as-is, as-designed, as-planned, as-constructed, as-built, and archived. The evolution of BIM model states from as-designed to archived follows established lifecycle definitions. Table 1 presents the key characteristics of each BIM model state. These states reflect progressively enriched model conditions informed by context-specific data and execution requirements. Since BIM models mature as projects progress, both modelling complexity and resource requirements increase substantially due to the need for cross-domain information reconciliation and real-time operability (Salzano, Miano, et al. 2023). Achieving high-fidelity LOD and LOIN requires a balance between representational granularity and implementation feasibility (Deng et al. 2021). Without this balance, modelling costs might be excessive without a proportional improvement in an operational utility.

Integrating BIM with digital twin

The ISO 19650 series essentially specifies the structured management of static BIM data and dynamic IoT data in the CDE of a BIM-enhanced DT. These ISO standards define a CDE as a controlled environment for managing information containers across the asset life cycle. The ISO 21597-1:2020

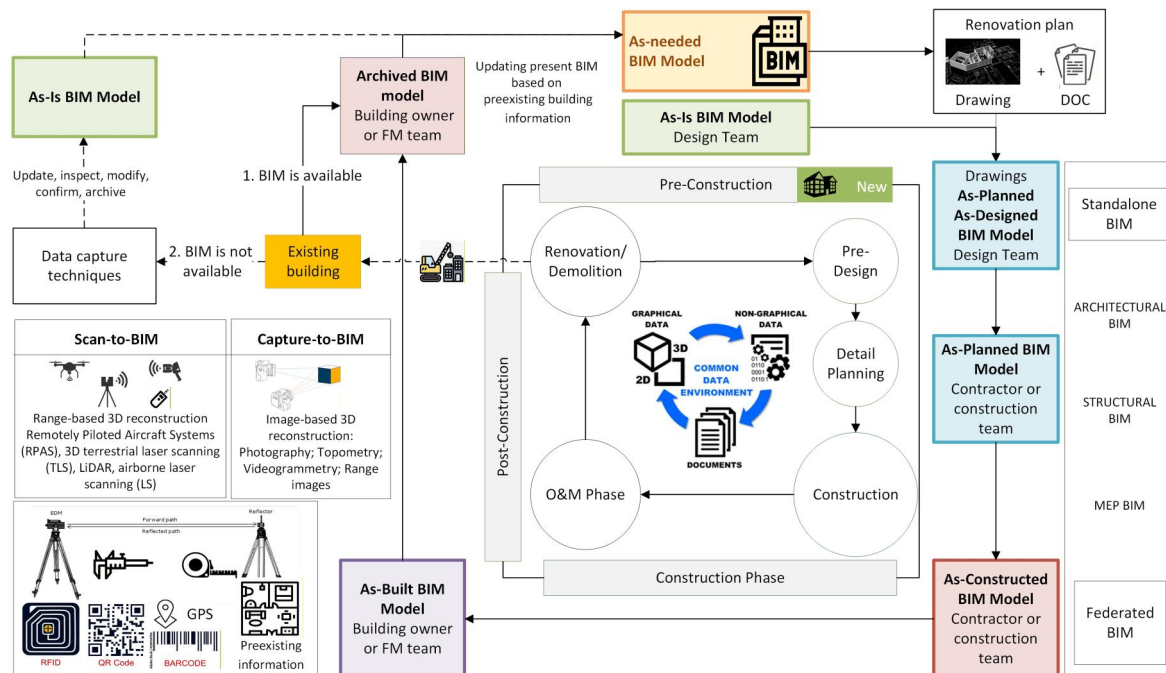


Figure 2. Six states of BIM models along a building's life cycle.

Table 1. Key characteristics of each BIM model state.

BIM model states	Key characteristics
As-designed BIM model (Kouch et al. 2018; Meng et al. 2020; Ferdosi et al. 2023; Banfi et al. 2025; Xia et al. 2025; Asare et al. 2026)	• Represents the intended building design before construction • Developed during the planning and design phases by architects and engineers • Contains 3D geometric information (LOD 100–300), spatial layouts, loads, systems, and Arch/Struct/MEP specifications • A federated structure of interdisciplinary models for statutory approvals, restoration strategies, and interdisciplinary coordination • Supports iterative design evaluation and visualization (spatial coordination, clash detection, energy analysis, and construction documentation, restoration strategies)
As-planned BIM model (Becker et al. 2019; Mengiste et al. 2024; Saif et al. 2024; Gao et al. 2026; Huang et al. 2026; Kinnen and Blankenbach 2026)	• Represents the intended construction execution and schedule, defining the expected project state before execution begins, detailing how and when the design will be built • Developed before project completion and handover by general contractors and construction managers. • Integrates as-designed geometry with time-bound data and overlays reality capture data onto the as-planned BIM model, enabling ‘scan-vs-BIM’ comparisons to detect geometric deviations and support multidisciplinary collaboration and risk mitigation • Baseline for planning, coordination, estimation and monitoring construction progress against the schedule
As-constructed BIM model (Edirisinghe et al. 2017; Daniotti, Lupica Spagnolo, et al. 2022; Everett and Gall 2022)	• Sometimes used interchangeably with ‘as-built’ • Captures the active state and deviations during construction and commissioning phases • Developed continuously by construction managers, contractors, subcontractors, and commissioning agents to resolve on-site clashes • Serves as a real-time record to validate execution accuracy • Defined by accuracy, completeness, interoperability, and security, ensuring dependable alignment with field conditions • Classified as ‘as-constructed assemblies’ that contain accurate information regarding their size, shape, location, quantity, and orientation • Includes field-verified data (product specs, serial numbers, installation dates, and O&M data) • Automation technologies can be used to improve model generation efficiency and precision. • Provides a reliable digital foundation that supports FM workflows and integration into DT environments
As-built BIM model (IFMA 2013; Lin et al. 2018; Daniotti, Lupica Spagnolo, et al. 2022; Everett and Gall 2022; Banfi et al. 2025)	• Sometimes used interchangeably with ‘as-delivered’ • Represent the finalized, field-verified version of the completed facility • Reflects all deviations from original design <i>via</i> reality capture (point clouds, imagery, construction records, and BIM datasets) • Delivered after occupancy to ensure all punch-list items are resolved • Serves as a final historical snapshot, the authoritative reference for O&M, FM activities, renovation planning, and historical tracking • Acts as a reliable foundation for DT applications requiring accurate, up-to-date, as-built information
As-is BIM model (BSI 2018c; Becker et al. 2019; Halmetoja 2020; Wang and Xiong 2021; Banfi et al. 2022; Daniotti, Pavan, et al. 2022; Nguyen et al. 2023; Mengiste et al. 2024; Revolti et al. 2024)	• Represents the current geometric and semantic conditions of an existing, in-use building without modifications, often in its ‘as-found’ state • Developed through reverse-engineering process (‘scan-to-BIM’) • Serves as a baseline for renovation, heritage conservation, or adaptive reuse • Primarily geometric; metadata is limited unless further enriched during post-processing • Often mapped equivalently to LOD 300–500 based on point-cloud density, but fundamentally differs as it captures existing reality rather than design intent. High LOD-G for visible surfaces, but LOD-I may be limited for hidden infrastructure due to occlusions • Reflects all real-world modifications, defects, and changes present in the built asset as a baseline for renovation, heritage conservation, or adaptive reuse • Provides reliable information for FM, renovation planning, and integration with DT workflows
Archived BIM model (IFMA 2013; BSI 2018a; Sepasgozar et al. 2023; Radzi et al. 2024; Abanda et al. 2025)	• Represents the final, inactive state of the project information container • Developed upon project handover or milestone completion within a CDE • Serves as a long-term digital record of the as-built condition for future reference and facility lifecycle needs and audit trail for legal and historical reference. • Provides exactly how the BIM model and its information containers developed over the course of the project • Prioritizes data integrity, accessibility, interoperability, and long-term sustainability of information • Functions as a DT reference model

document complements this ISO series by standardizing the structure and referencing of distributed documents and data using container metadata files (CMFs) and link files in formats such as XML and JSON. These mechanisms allow explicit linking between BIM models, real-time sensor streams, and

external sources (e.g. point clouds), enabling semantic consistency and traceability across heterogeneous datasets. Within this integrated environment, a CDE serves as a federated platform for ingesting and organizing real-time data collected from the data acquisition layer, allowing shared information containers to synchronize IoT sensor inputs with BIM components (El-Din et al. 2022). This supports advanced DT functions such as automated anomaly detection, condition monitoring, and predictive decision-making using machine learning. Feedback loops are established through actuators or linked control systems when predefined thresholds are exceeded. However, research on CDEs fully integrated with DTs remains limited, as DTs introduce significantly more complex, high-frequency, and non-structured data than traditional BIM workflows (Yan et al. 2022).

Integrating BIM with DT in a CDE introduces an additional layer of complexity across technological, organizational, and cognitive domains (Camposano et al. 2021). Ali and Bandi (2024) reported a moderate inverse correlation between operation and maintenance (O&M) dataset usability and big data alignment within BIM platforms, highlighting the need to streamline data pipelines to minimize redundancy and enhance system scalability. To support high-performance O&M systems, several research works investigated BIM-integrated asset management platforms, enabling proactive maintenance, contextual decision support, and structured information retrieval (Likhitrungsilp et al. 2022). Nevertheless, they remained limitedly adopted by the industry due to insufficient stakeholder engagement, ambiguous performance validation frameworks, and the lack of standardized protocols for embedding BIM into DT-enabled environments (Mohammed et al. 2022).

Table 2 compares various BIM-enhanced DT architectures, which consistently emphasize the fusion of BIM, IoT, and analytics to enable real-time, data-informed decision-making throughout the asset life cycle. As can be seen, they consist of four common layers: (1) physical-to-digital data acquisition, (2) processing and synchronization pipelines, (3) decision-support and analytics modules, and (4) user interface dashboards. Beyond representation and visualization, the integration of artificial intelligence (AI) and cognitive technologies transforms these into cognitive DTs (CDTs) (D'Amico et al. 2024). By semantically aligning IFC-based BIM models with IoT-derived time-series data, these systems create unified, machine-interpretable knowledge bases. This convergence enables AI-assisted reasoning, real-time situational awareness, and data-informed decision-making throughout the asset lifecycle (Pauwels et al. 2024).

Research methodology

In this paper, we developed the architectural configuration of a BIM-enhanced DT for real-time construction pollution management in building renovation projects. The primary objective is to delineate the minimum BIM modelling requirements, particularly those related to LOD and LOIN, which are necessary for real-time environmental monitoring within the context of building renovation projects.

The system architecture was initially derived from our literature-based synthesis, establishing a theoretical foundation for developing a BIM-enhanced DT from unstructured non-BIM elements. This process revealed key gaps in current practices, CDE components, and minimum modelling requirements (LOIN-LOD for renovation-specific monitoring), particularly in how these gaps hinder effective real-time environmental monitoring and integration with existing systems. The findings consolidated fragmented knowledge into structured concepts, defining core components of the BIM-enhanced DT architectural framework. We further evaluated the functional and technical characteristics of digital representation systems, including bidirectional data flow, semantic metadata layering, interoperability standards (e.g. ISO 19650 and IFC), and feedback mechanisms for dynamic environmental performance control.

Building upon the aforementioned insights, we introduced a novel LOIN schema. This schema integrates geometric modelling levels (LOD-G) with corresponding informational layers (LOD-I), facilitating structured information delivery throughout the project life cycle, from initial modelling to real-time monitoring and decision-making. The proposed LOIN framework supports systematized pollution information capture, enabling enhanced traceability, sensor placement optimization, and regulatory compliance tracking.

Table 2. Different BIM-enhanced DT architectures and core components.

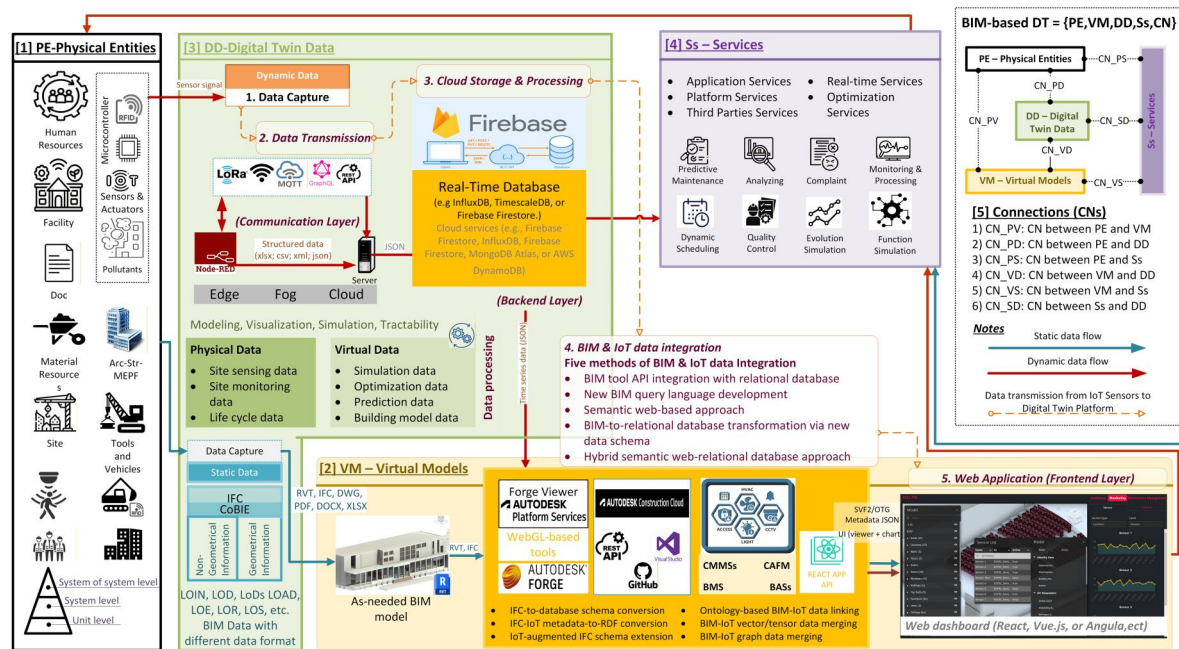
Aspect	Architectures and components	Sources
Multidimensional DT architecture	Defined as MDT = (PE, VM, Ss, DD, CN) where PE denotes physical entities, VM refers to virtual models, Ss represents services, DD corresponds to DT data, and CN signifies system connections	Tao and Zhang 2017 ; Qi and Tao 2018 ; Tao, Zhang, et al. 2019
Core IoT layers	Comprises four primary layers: sensing, network, data processing, and application. These enable end-to-end DT functionality from data acquisition to visualization.	Tao, Qi, et al. 2019 ; Wang et al. 2022 ; Chung et al. 2023
Five-part DT structure	A DT framework comprises: (1) virtual representation of the physical entity, (2) physical-to-virtual data flow, (3) virtual feedback to physical systems, and (4) specialized service provision.	Jiang et al. 2021
Five-layer architecture	Includes cyber-physical, data processing, computational, functional, and visualization layers for integrated DT modelling	Hu et al. 2022
DT information system workflow	Organized into three concentric control cycles: data stores, processing modules, and monitoring technologies	Sacks et al. 2020
DT system architecture for building/city levels	Structured into six layers: data acquisition, transmission, digital modelling, data-model integration, service delivery, and user interaction	Lu et al. 2020
DT ecosystem	Defines DT prototypes (DTP), instances (DTI), and cyber-physical systems (CPS), with a focus on data fusion and lifecycle support	Sepasgozar 2021
Core DT components	Digital representations of construction assets integrated with IoT, analytics platforms, and interaction modules. Conceptualized as a map of physical, digital, and application domains	Zhang et al. 2022
Basic architecture	Encompasses BIM-enhanced representation, IoT data acquisition, cloud analytics, and visualization platforms	Zhang et al. 2022
Components of DT	Combines BIM models, IoT networks, cloud data infrastructure, analytical engines, and user interface layers	Eneyew et al. 2022
Five key elements of DT	Scenario (SC), virtual entity (VE), physical entity (PE), relationship (RL), and component (CO)	Tao et al. 2022 ; Li et al. 2024
DT system structure	Integrates IoT hardware, middleware for data orchestration, and AI-based engines for analysis and decision support	El-Agamy et al. 2024

To ensure practical relevance and stakeholder alignment, the framework was refined through semi-structured interviews (45–90 min) (Fellows and Liu [2015](#)) with nine experts across three distinct cohorts. [Table 3](#) summarizes the interviewees' profiles. The transcripts were analyzed to extract domain-specific requirements concerning platform design, interoperability challenges, and real-time data exchange protocols. The insights from the interviews identified BIM-enhanced DT components, clarifying their roles in pollution monitoring as well as deepening our understanding of BIM and its usage for the DT development. The integration of academic and practitioner perspectives guided the CDE design, addressing major challenges in data governance, interoperability, and platform applicability. These verifications revealed key implementation challenges of the preliminary framework, including the different alignment of information protocols in new construction and renovation projects, divergent CDE workflows, and stakeholder-specific expectations regarding data granularity and integration. Herein, we primarily focused on the EIR and bidirectional data workflows of the proposed system to ensure semantic consistency across all platforms.

The derived platform was then applied to an actual renovation project on Chulalongkorn University campus, Bangkok, Thailand. Due to its location in a high-density academic complex, the project required strict environmental quality control to minimize pollution, ensure comfort for university staff and students during teaching activities, safeguard the health and safety of on-site construction workers, and preserve the structural integrity of the building. A pilot test was implemented by installing six IoT sensor clusters in sensitive areas (e.g. corridors, construction zones, and mechanical rooms) to gather noise level, PM_{2.5}, CO₂, and vibration sensory data. The implementation demonstrated the system's fidelity and capability to collect, transmit, process, visualize, and simulate environmental data within the designed solution. It also assessed the viability of the LOIN-LOD structure in supporting real-time environmental feedback on the platform. Additional information about this system can be found in Pham ([2023](#)), Pham and Likhitrungsilp ([2023](#)), Pham et al. ([2024, 2025](#)), and Likhitrungsilp et al. ([2025](#)).

Table 3. Interviewees' profile.

Specialization	Years of experience	Work location	Expertise areas
1. Project manager	20	Thailand	Construction project management
2. Project manager	15		
3. Site manager	12		
4. Civil engineer, BIM manager, and web developer	10	Vietnam	Construction data integration, on-site coordination, and digital workflows BIM for civil infrastructure, IoT integration in construction, Web development and management, Revit API, Forge API
5. Civil engineer and BIM expert	7		BIM modelling and coordination, digital asset lifecycle management, architectural visualization
6. Electronics engineer and system engineer	7	Taiwan	Electrical systems engineering and telecommunication, IoT hardware/software integration, data management, and networking
7. Environmentalist	22	Thailand	Water and wastewater treatment, ultrasound applications in environmental monitoring, sustainable infrastructure
8. Environmentalist	32		Air pollution modelling, particulate matter analysis, environmental impact assessment (EIA), sustainability planning
9. Environmentalist	22		Indoor and outdoor air quality management, sustainable energy solutions, environmental sensor technologies

**Figure 3.** BIM-enhanced DT architecture for pollution management in building renovation projects.

BIM-enhanced digital twin architecture

Inspired by the preceding platforms (Qi and Tao 2018; Tao, Zhang, et al. 2019; Wu et al. 2021; Hu et al. 2022), the proposed BIM-enhanced DT architecture was defined by five interoperable components: physical entities (PEs), virtual models (VMs), services (Ss), DT data (DD), and connections (CNs), as illustrated in Figure 3. This DT architecture was designed to systematically and efficiently process both static data provided by BIM models and dynamic data from IoT sensors for real-time pollution monitoring at renovation sites. The details of each platform component are as follows.

Physical entities (PEs)

PEs constitute the tangible elements of the construction environment, including building components, construction equipment, mechanical systems, human agents, and site-specific environmental factors,

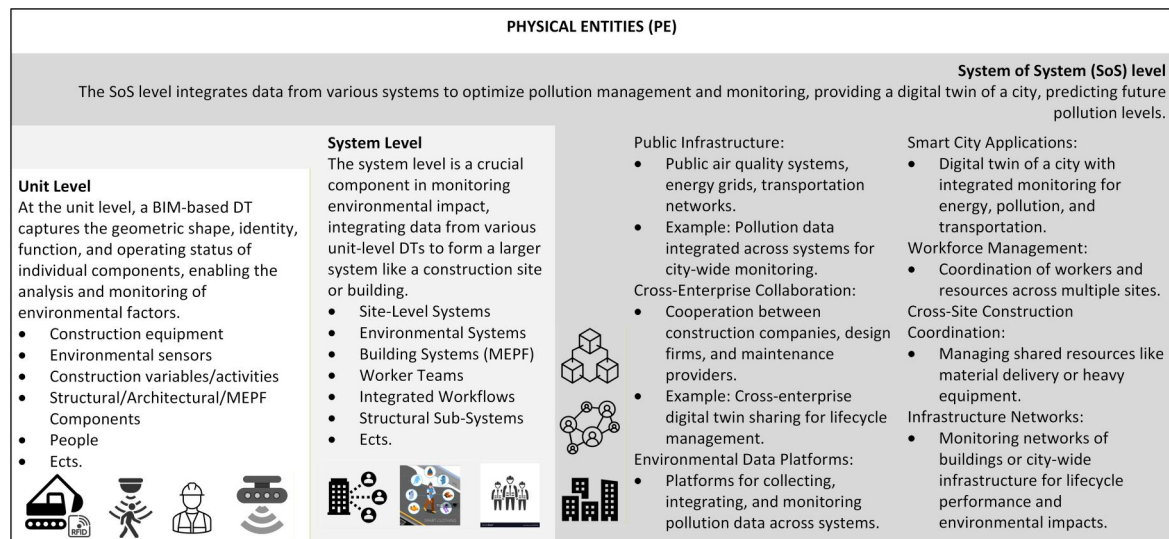


Figure 4. Classification of the PEs in the DT platform across the unit, system, and system-of-systems (SoS) levels.

which are responsible for or affected by pollution events (Becker et al. 2019; Tao, Qi, et al. 2019; Hong et al. 2020; Ushakov et al. 2022; Chung et al. 2023). PEs serve as the starting and ending points of the information flow loop. They represent where data is collected and processed, as well as stakeholder-driven decision-making aligned with the intended use of the DT.

These entities can be digitized *via* IoT sensors, which stream real-time environmental data into the DT system for real-time processing. The classification of PEs can be structured across three hierarchical levels: unit, system, and system-of-systems (SoS), as shown in Figure 4.

Virtual models (VMs)

VMs are the digital surrogates of PEs, capturing geometric, behavioural, and semantic attributes to support real-time environmental simulation. In building renovation contexts, VMs enable dynamic visualization of pollutant dispersion, simulate air flow, and inform zone-specific risk analysis. They can be constructed by using a suite of tools (e.g. BIM, GIS, MR, and CAD) and structured into the following four modelling layers (Tao and Zhang 2017; Tao et al. 2018; Sepasgozar et al. 2023):

- *Geometric models* represent the spatial configuration of built assets, which enables pollutant visualization and sensor placement planning.
- *Physical models* simulate environmental interactions based on material properties and pollutant emission dynamics.
- *Behavioural models* capture the temporal change and interaction of pollution sources and environmental conditions.
- *Rule-based models* encode thresholds, standards, and expert knowledge to inform compliance-driven simulations.

This layered modelling architecture enhances system interpretability and supports scenario-based analysis aligned with regulatory and operational constraints.

DT data (DD)

DD integrates static and dynamic data derived from PEs, VMs, expert knowledge, and fusion data to offer a comprehensive understanding of on-site pollution behaviours. This integration encompasses forecasting, automated alerts, and visual dashboards (e.g. time-series graphs and heatmaps). It also

includes knowledge data (historical and threshold-based rules) and fusion data (multi-source integration) for enhancing modelling precision.

- *Static data* includes BIM-derived attributes, CAD documents, regulatory standards, and historical pollution datasets. This type of data defines baseline modelling and scenario simulation without real-time synchronization.
- *Dynamic data* comprises live sensor feeds and contextual inputs (e.g. resident complaints), streamed via IoT infrastructure.
- *Knowledge data* encodes expert rules, compliance thresholds, and historical trend logic to guide predictive responses.
- *Fusion data* integrates heterogeneous inputs from static and dynamic sources to enhance analytic precision and system scalability.

To integrate all the data above, the DT system employs VMs to conduct scenario-based simulations and generate predictive outputs. These outputs support environmental compliance, operational risk mitigation, and stakeholder communication. In the CDE workflow, both static and dynamic information flows are systematically structured and organized in information containers. Each represents the state in data management, validation, and dissemination (Pham et al. 2025). Static information, such as material properties, directly influences the type and quantity of pollutants released during renovation activities, whereas demolition timing determines when specific areas are exposed to potential emissions. By organizing this data within the construction workflow, each object in the model can be linked to sensor locations and environmental thresholds in the DT. This linkage allows the system to continuously compare predicted pollutant levels to real-time measurements, generate alerts, and support mitigation strategies like ventilation adjustments or sequence optimization.

Furthermore, the organized BIM data enables dynamic scenario simulations, allowing stakeholders to evaluate alternative materials and demolition sequences as well as to predict their environmental impacts before implementation. In this way, integrating BIM static information with workflow design directly improves the DT's predictive and adaptive capabilities for effective pollution management. The comprehensive structure of DD guarantees that the system remains context-aware, interpretable, and scalable across renovation scenarios.

Services (Ss)

Ss represent the actionable layer of DT systems, translating integrated data into environmental insights, mitigation strategies, and compliance documentation. They rely on effective DD metadata usage to deliver actionable insights for pollution management. Tao, Qi, et al. (2019) and Hu et al. (2022) defined three categories of services:

- *Application services* constitute the core operational capabilities of the DT, enabling a performance assessment through functionalities such as simulation, verification, monitoring, optimization, diagnostics, and predictive analytics.
- *Third-party services* augment core specialized analytical capabilities by integrating external algorithms, datasets, and expert knowledge to enhance decision-making in pollution mitigation scenarios.
- *Platform services* provide the systemic interface between BIM-enhanced models and IoT-enabled sensor networks, supporting real-time data flow, resource optimization, and environmental performance tracking.

Each service tier operates on the DD architecture and supports stakeholder-specific applications across the renovation life cycle.

Connections (CNs)

The DT platform can be interconnected through six bidirectional connection (CN) pathways: (1) CN between PE and VM (CN_PV), (2) CN between PE and DD (CN_PD), (3) CN between PE and Ss

(CN_PS), (4) CN between VM and DD (CN_VD), (5) CN between VM and Ss (CN_VS), and (6) CN between Ss and DD (CN_SD). They facilitate real-time data flow between the core components, as shown in Figure 3. These CNs ensure semantic consistency, support automated alerts, and maintain system responsiveness under variable site conditions. They connect not only the other five core components but also the integration methodology for combining dynamic and static data in the CDE solutions.

LOIN for an as-needed BIM model

Data drift between analytical knowledge bases and the authoritative BIM model presents a significant challenge, particularly when large volumes of information accumulate (Alsehray et al. 2025). Addressing this issue requires a transition toward an as-needed BIM model. In the DT application, the LOIN is preferred over the traditional LOD/LOI as it provides a purpose-driven methodology that avoids information redundancy (Collado-Mariscal et al. 2025). The information defined by LOIN for an as-needed BIM model serves as a fundamental reference for additional functions in the proposed platform. Within this approach, the LOIN framework ensures that only precise, task-specific information is generated and maintained for complex reasoning, advanced data analysis, and informed decision-making (Kone and Mahesh 2025). This ensures information reliability at key milestones and prevents stakeholders from over-relying on immature data.

Effective pollution monitoring requires BIM models within the DT environment to evolve beyond static geometric representations and support real-time responsiveness and data-driven decision-making. Although LOD and LOIN serve distinct functions, they are inherently complementary. As depicted in Figure 5, LOD provides geometric fidelity necessary for sensor deployment and spatial simulation, while LOIN governs semantic requirements such as information type, delivery format, and use-case relevance across project phases. To operationalize these capabilities, a hybrid LOIN-LOD structure was introduced to incorporate both geometric (LOD-G) and informational (LOD-I) dimensions. The proposed framework synthesizes the insights derived from the expert interviews and the previous platforms (e.g. Gökğür 2015; Helander and Singh 2016; BSI 2018b, 2018c; Daniotti et al. 2020; Elagiry et al. 2020; Bolpagni and Hooper 2021; Daniotti, Lupica Spagnolo, et al. 2022; Daniotti, Masera, et al. 2022; Ismaeel et al. 2023; Pham 2023; Pham and Likhitrangsilp 2023; Salzano, Parisi, et al. 2023; Spudys et al. 2023; Pham et al. 2024, 2025). Detailed discussion on LOD-I and LOD-G can be found in Pham et al. (2024).

Figure 6 illustrates the minimum LOIN requirements for the BIM models in the proposed DT platform. The important insights concluded from the interviews with each expert group are as follows.

- The stakeholders emphasized the necessity of real-time alerts, zone-specific visualization, and threshold-triggered notifications to support operational responsiveness.
- The BIM-IoT experts highlighted the importance of metadata, including sensor calibration logs, transmission intervals, and communication protocols, for achieving seamless system integration. Their guidance directly shaped the structure of connection pathways, especially CN_PV, CN_VS, and CN_SD, ensuring the seamless data exchange and the interoperability within the DT ecosystem.

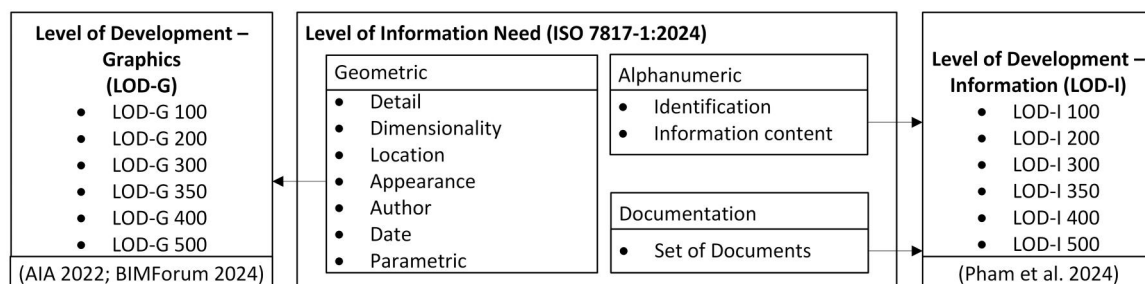


Figure 5. Complementary integration of LOIN and LOD for the BIM-enhanced DT.

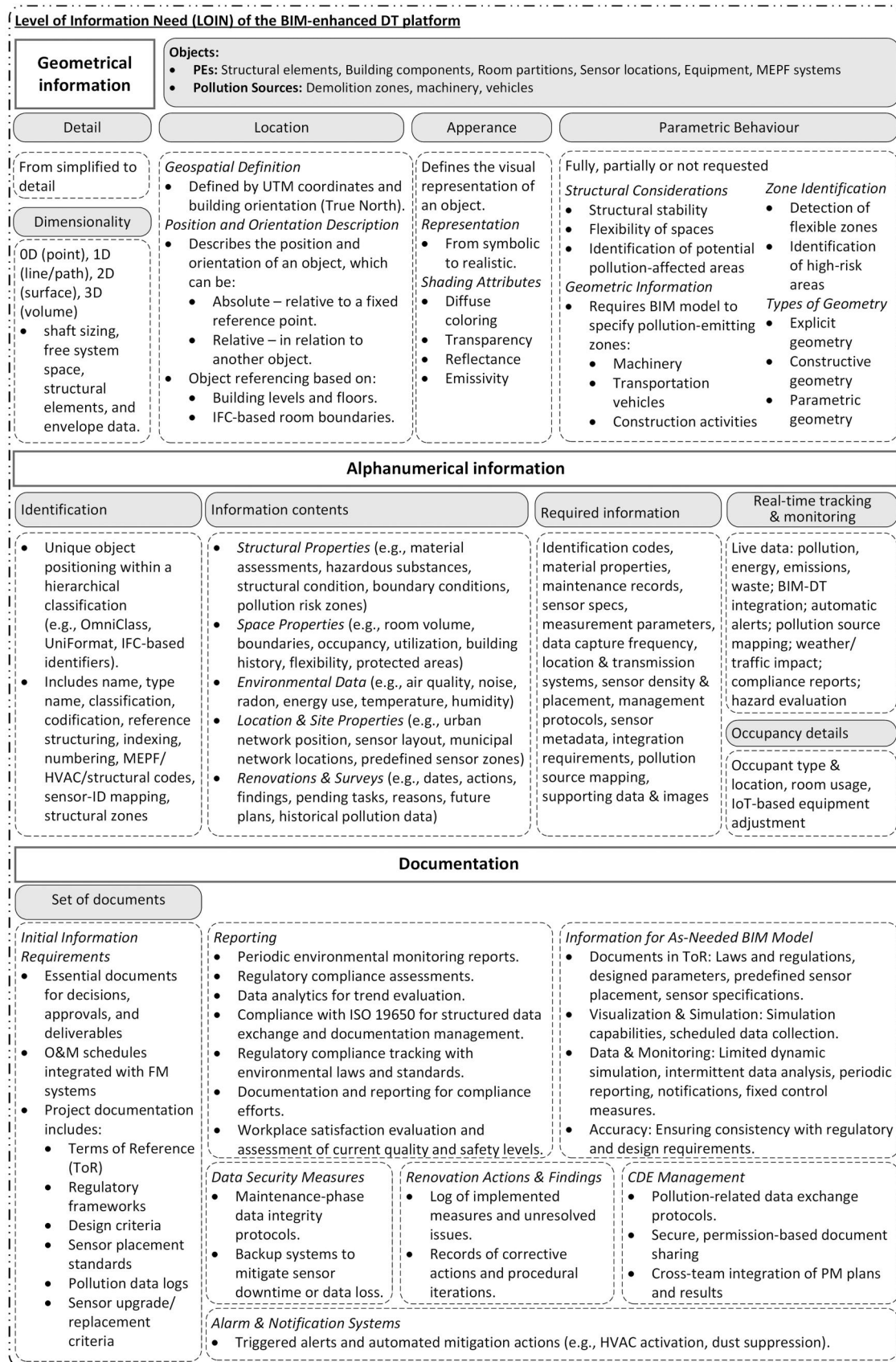


Figure 6. Level of Information Need (LOIN) of the BIM-enhanced DT platform.

- The environmental specialists focused on regulatory benchmarks and contextual variables (e.g. weather patterns and urban topography), defining the development of rule-based VM models and compliance-linked outputs.

By incorporating the experts' insights, the LOIN framework was extended to support additional functionalities, including real-time BIM visualizations of pollution events, automated alerts based on regulatory thresholds, and spatial association between sensor readings and architectural elements. This hybrid LOIN-LOD structure allows the DT architecture to be scalable, interoperable, and aligned with stakeholder-specific needs throughout renovation projects.

Application of the BIM-enhanced DT platform

The proposed BIM-enhanced DT platform was applied to the renovation project of an auditorium at Chulalongkorn University campus, Bangkok, Thailand. This application aimed to verify the CDE, IoT-BIM integration, and rule-based automation of the proposed system. To evaluate the system's efficacy, the following capabilities were assessed:

- *Continuous transmission of reliable environmental data with real-time notifications* to ensure timely alerts when pollutant levels (e.g. PM_{2.5}, CO₂, and noise) surpassed safety limits.
- *Supporting comprehensive data handling*, including the acquisition, transmission, visualization, simulation, analysis, and secure storage of environmental data, enabling real-time monitoring and informed decision-making.
- *Provision of spatial context*, ensuring each monitoring device was accurately placed and its data was correctly contextualized within the BIM environment.
- *Evidence-based decision support*, enabled through the integration of real-time environmental data into the project management workflow, which supports informed decision-making and requires construction parties to propose and implement data-driven mitigation strategies to reduce pollution sources.

We first defined the project information requirements, the definition of information exchange protocols, and the clarity of EIR among the involved stakeholders. Based on the proposed LOIN, we applied the schema to the case study. An as-needed BIM model of the facility was developed with the proposed LOIN to support the BIM-enhanced DT. A pilot test for the CDE solution was then carried out. The CDE workflow and solution were adapted from those of Pham and Likhitrungsilp (2023), Pham et al. (2024, 2025), and Likhitrungsilp et al. (2025) with further methodological elaboration. Figures 7–12 sequentially illustrate the operational scope of the proposed platform. They demonstrate how physical renovation constraints are transformed into a spatially contextualized digital twin, and how the resulting BIM state is developed through the process of constructing an as-needed BIM model from the as-is BIM model (derived from scan-to-BIM) and as-designed renovation drawings. These figures further present the definition of LOIN-LOD for the as-needed BIM model, which is subsequently utilized for digital twin development, rule-based automation, and live environmental monitoring services. Collectively, they document the platform's capability to bridge the gap between physical site conditions and digital twin functionalities, demonstrating the practical implementation of LOIN specifications and real-time IoT-BIM synchronization within a unified monitoring interface.

Figure 7 shows the PEs of the platform, including structural zones, construction equipment, and monitored environmental areas. Due to the absence of legacy BIM documentation, an as-is BIM model of the auditorium was created using a scan-to-BIM approach, as shown in Figure 8(a). This BIM model conformed with an LOD-G of 200 for the baseline representation, as shown in Figure 8(b). This foundational model was subsequently advanced to an as-designed federated BIM model with LOD-G 350 to facilitate clash detection across architectural, structural, and MEP systems, as shown in Figure 8(c), supporting the operationalization of the DT platform.

Figure 9 illustrates the VMs of the BIM-enhanced DT system. Figure 9(a) shows the layout of the renovation site, including the relative positions of the occupied adjacent areas during renovation.



Figure 7. Physical entities (PEs) of the BIM-enhanced DT system.

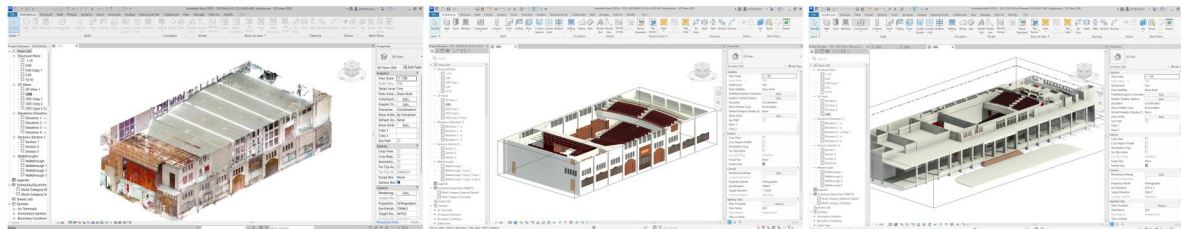


Figure 8. Federated as-needed BIM models used for DT development: (a) point cloud, (b) as-is BIM model with LOD-G 200, and (c) as-designed BIM model with LOD-G 350.

Figure 9(b) illustrates the defined *IfcSpaces* within the BIM model for the internal zones on the ground floor. The internal zones were enclosed areas where monitoring IEQ was essential to protect occupant health and maintain productivity. The external zones were also investigated to identify pollution sources, such as spray-painting and welding activities. Figures 9(c,d) illustrate the installation of vibration sensors on structural walls. These sensors were defined as *IfcSensor* entities in the BIM model, enabling their seamless linkage and real-time data integration within the CDE for assessing construction-induced vibration.

In the as-needed BIM model, sensor clusters were represented at LOD-G 200, which did not require detailed geometry but demanded logical associations with host elements. For example, sensor cluster 7W was mounted on *Wall ID01*. Spatial positioning was precisely defined through coordinate-based placement and spatial classification, including internal and external zones, floor levels, and room boundaries. Each sensor cluster was uniquely defined by labels and numeric codes with metadata describing its function, host component, and operational parameters embedded within sensor families. The *IfcSensor* entity was used with the predefined type of set to ‘*UserDefined*’ to accommodate custom sensor characteristics (i.e. dust, noise, vibration, and air quality).

Sensor metadata was enriched with alphanumeric attributes and linked with real-time data streams via an IoT integration layer utilizing MQTT protocol and Firebase. This metadata comprised sensor identifiers, measured parameters, sensor types, communication protocols (e.g. Wi-Fi), physical locations (e.g. room, host surface, and spatial coordinates), and data stream references such as MQTT topics and APIs. The environmental monitoring on the site was executed through a Node-RED flow-based programming interface, entailing real-time data acquisition and processing, as displayed in Figure 10. A rule-based logic engine within Node-RED automatically assessed sensor data against predefined regulatory thresholds, triggering alerts via email and mobile push notifications to designated stakeholders upon exceedance events, as shown in Figure 11.

The data concerning PM_{2.5} concentrations, noise levels, and vibration intensity was transmitted via an MQTT protocol to both local servers and Firebase cloud services, ensuring dual-layered data storage. Calibrated sensor information was manually recorded and stored locally on computer memory. The hybrid data management architecture facilitated a seamless integration between Autodesk Forge (handling BIM-enhanced spatial data) and Firebase (handling real-time sensor streams). Firebase

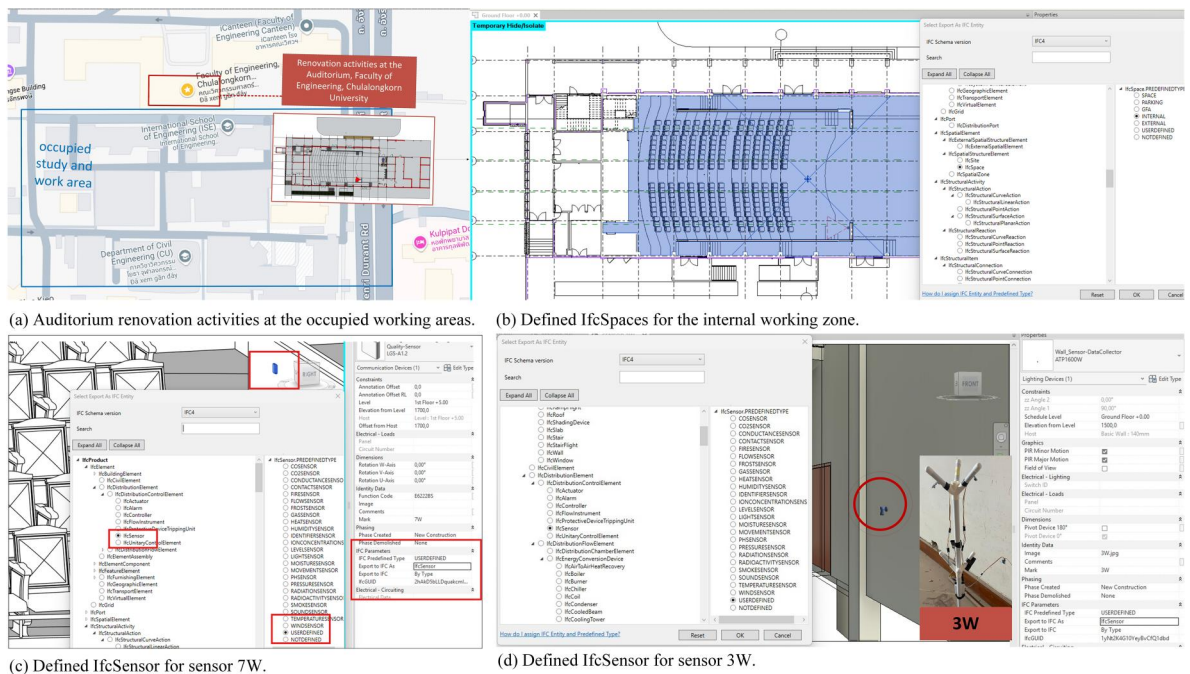


Figure 9. Virtual models (VMs) of the BIM-enhanced DT system.

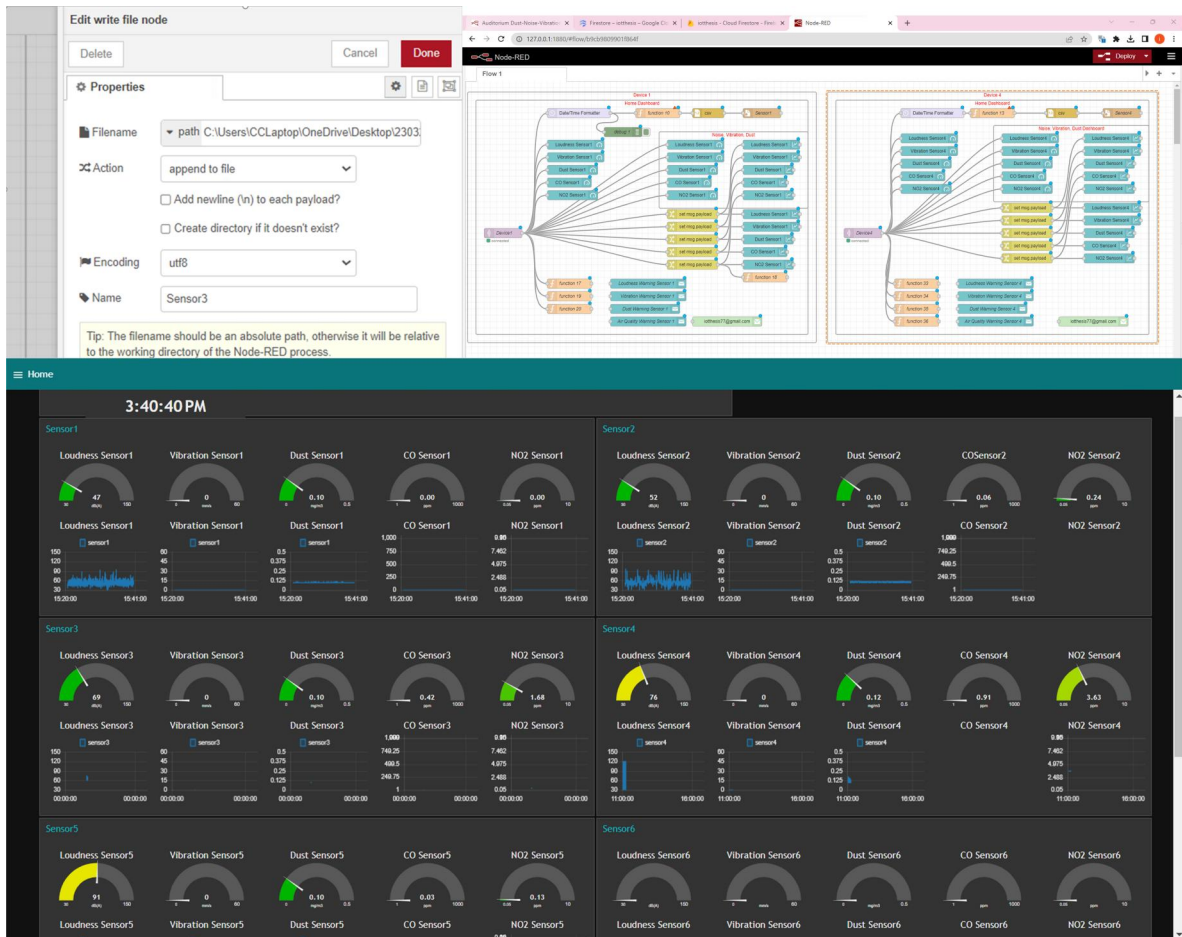


Figure 10. Node-RED Interface for flow-based programming and real-time data transmission.

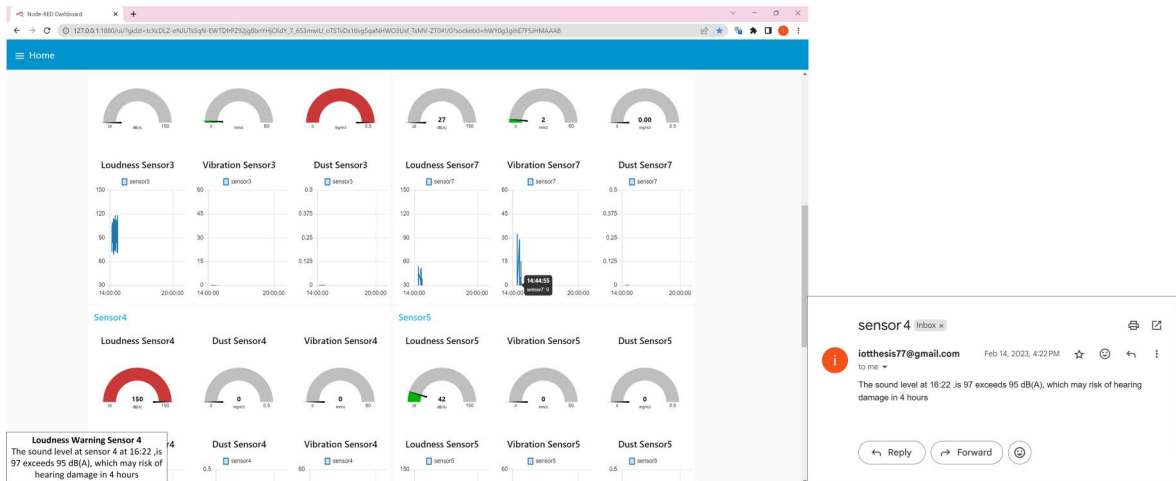


Figure 11. Automated alert system triggered by regulatory threshold breaches.

components, including Firestore, real-time database, and cloud functions, ensured secure, low-latency synchronization between static BIM attributes and dynamic sensor inputs. The seamless integration of sensor data into a Firebase cloud storage database enabled the transmission of environmental data with scalability, security, and ease of access. All data and notifications were systematically stored as verifiable evidence, empowering stakeholders to make informed decisions, track compliance, and implement timely corrective actions.

The sensor records stored in Firebase were used to dynamically adjust pollutant threshold values based on the reliability metrics of each sensor. This mechanism ensured that real-time decision-making processes reflected both sensor performance history and operational stability. This interoperability facilitated the rendering of a real-time DT dashboard created by React.js. It allowed project stakeholders to visualize environmental metrics within the spatial context of the BIM model, as shown in Figure 12. This configuration provided decision-makers with a contextualized, real-time interface to support monitoring, communication, and adaptive environmental control.

Discussion

Traditional methods, such as manual inspections or periodic sampling with handheld devices, offer low temporal resolution and often involve delays of several days between data collection and reporting. This leads to prolonged exposure due to undetected exceedances between inspections. On the contrary, the BIM-enhanced DT solution provides automatic alerts that trigger immediate mitigation actions. It delivers immediate feedback through continuous monitoring at 1-s intervals *via* the IoT solution and provides near-real-time updates on the website. Automated updates improve coordination across shift-based teams, reducing delays, enhancing communication, and ensuring smoother transitions.

In this case study application, the system enabled continuous monitoring during renovation, with sensors transmitting data every second to a live database. This automated flow supported real-time progress tracking *via* the monitoring web and dashboard. Gauge charts provided instant visual feedback on safe limits for faster decisions, while line charts revealed historical trends, anomalies, and correlations. Visualized data on dust, noise, and vibrations supported early risk detection and proactive workflow adjustments. The combined use of gauge and line charts with spatial information enhanced situational awareness, enabled early warnings, and informed interventions based on both real-time conditions and emerging patterns.

The evolution from 3D BIM to integrated BIM (iBIM) and DT can be evaluated based on how consistently and dynamically a VM reflects its corresponding physical asset. In this context, LOIN serves as a standardized mechanism to ensure that the digital twin contains the precise information required to achieve these advanced levels of maturity. Enhanced BIM uses LOIN principles to ensure that specific end users receive only the precise quality and quantity of information needed for their roles. Our

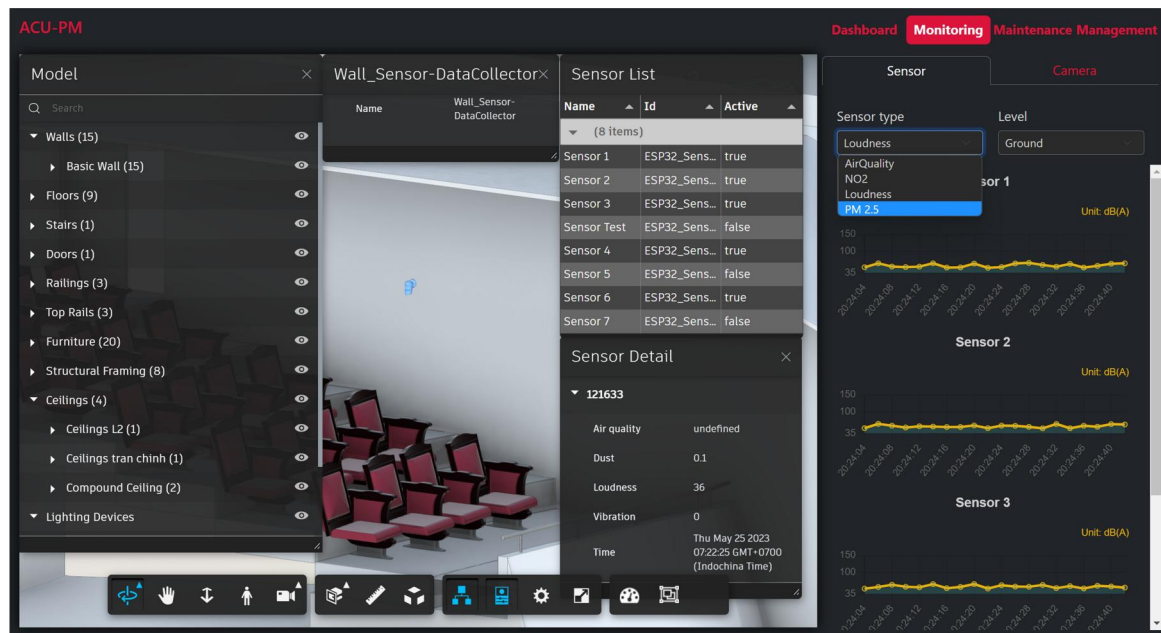


Figure 12. React-based DT dashboard integrated with Autodesk Forge for real-time visualization.

hybrid LOIN-LOD findings underscore that aligning VM and DD with strategic Ss is not merely a technical necessity but a critical enabler of value-driven asset management. By defining precise LOIN with sufficient LOD-G (geometric) and LOD-I (informational) requirements, stakeholders know exactly what data the facility manager needs to run their mature DT systems (like CMMS or IoT dashboards) before the project is handed over. They can avoid redundant LOD-I data collection and over-modelling LOD-G that increase cost and time without adding value. The as-needed BIM model that archives managed information provides a structured, purpose-driven approach to using building information to manage physical assets long after construction is finished. This approach ensures that asset information is directly relevant to daily operational tasks and strategic decision-making.

For the IoT integration in CDE, defining the minimum LOIN for BIM-based DT usage facilitates the identification of information requirements for sensor data schemas, defines the scope of IoT sensor networks, and specifies standards for representing data. It ensures that dynamic IoT data and static metadata from IoT systems are integrated coherently into the DT, supporting real-time monitoring, decision-making, and the extraction of IoT-related concepts for analytical or operational purposes. This structured approach is further operationalized through Information Delivery Specifications (IDS) and standardized data dictionaries like bSDD, creating machine-readable, interoperable datasets (Wang Y et al. 2024; Fischer et al. 2025). This standardization is essential for achieving higher DT maturity, enabling advanced analytics, and supporting predictive operational decision-making, moving beyond mere geometric representation to ensure the model's operational integrity and analytical utility.

In the development of an IFC-based system in a BIM workflow, LOIN defines the creation of accurate geometric representations and supports semantic and textual mapping across different systems. Defining LOIN and corresponding LOD for BIM and IFC models gives semantic technologies (semantic ontologies and knowledge graphs) a strong base to build on for future uses. Such a semantic integration enables the development of cognitive DT systems capable of supporting automated, system-of-systems decision-making, thereby linking high-level architectural frameworks with real-time, context-aware operational intelligence. It enables the system to interpret, reason, and adapt to complex operational scenarios, creating opportunities for leveraging AI to support predictive analytics, automated decision-making, and intelligent management of construction and renovation processes. In this sense, the architecture represents a step toward a more cognitively aware and AI-enabled DT paradigm, bridging the gap between conventional BIM-DT applications and advanced, context-sensitive intelligent systems.

Contribution and limitation

The maturity of DT systems is determined not only by the integration of real-time data but also by the consistency between BIM states, nD dimensions, and structured information requirements. While existing implementations often extend BIM models closer to the as-is state by incorporating multi-dimensional data (e.g. 3D geometry to 8D occupational safety and nDs iBIM model for DT applications), sensor-driven data acquisition, and expanded data connectivity, they frequently lack mechanisms to control information relevance and quality. Consequently, the progression toward an intelligent DT is not solely driven by data acquisition but by the ability to structure and constrain information effectively. This study addresses this limitation by introducing a LOIN-based framework that governs the specification, structuring, and management of information within the BIM database, thereby enabling a more robust transition from static BIM representations to intelligent, data-driven DT environments.

The proposed system fills the research gap between static building documentation and operational responsiveness by incorporating real-time environmental data into the BIM environment. Firstly, it transforms pollution management from reactive diagnostics to proactive control enables automated mitigation through spatially linked dashboards, threshold-triggered alerts, and regulatory reporting protocols. The proposed BIM-enhanced DT platform delivers actionable tools integrating semantically enriched BIM models, IoT-integrated data streams, and context-sensitive response mechanisms suitable for real-world renovation applications.

Secondly, our DT platform advanced the conceptualization of information requirements across the project life cycle by distinguishing the needs of new construction projects from those of renovation projects. This knowledge is valuable in enhancing the adoption of digital asset management in the built environment. The hybrid LOIN-LOD framework supports the transition from any existing state of a BIM model to an as-needed BIM model, reducing unnecessary data generation and mitigating the problem of information for information's sake. This approach ensures that only the information necessary to support specific project objectives, environmental monitoring, or regulatory compliance is captured and maintained.

The technology implementation enables stakeholders to make decisions promptly while reducing risks concerning structural integrity and workers' safety. The alignment of BIM LOIN-LOD with DT classes and data maturity has increased the understanding of how BIM contributes to DT development and clarifies the LOIN requirements for DT implementation. The integration of BIM, IoT, and cloud-based automation verified the platform's potential for broader deployment across similarly constrained retrofit scenarios, especially where pre-digital building environments and strict environmental compliance intersect. This platform can reduce the burden on data acquisition and model development. It can also enhance transparency among stakeholders by clarifying the scope of work and responsibilities from the outset. The early definition of appropriate LOD-G provides a practical basis for BIM implementation, particularly when integrating IoT systems within the BIM model.

Even though our research can successfully fill several crucial research gaps, it entails several limitations that have not yet been addressed, such as complaint management and participatory mitigation strategies. The proposed framework includes an HVAC-MEPF system integration and actuators designed to mitigate dust pollution during construction activities by automating responses when pollution exceeds the thresholds. Yet the implementation in this research remains limited. Due to time and budget constraints, the system cannot perform construction progress tracking and the complaint reception channel. Besides, while LOIN for the as-needed BIM model and the architectural framework has been defined, the semantic representation and ontology-based integration have not been fully explored, leading to limited applications in automation data preprocessing, semantic interpretation, and intelligent control execution.

User interface and decision support are also our major challenges. For example, visualizing large datasets on Autodesk Forge created performance bottlenecks. Site managers preferred simplified key performance indicators over raw sensor feeds. To improve usability, dashboards were optimized to display aggregated KPIs such as compliance rates and exceedance frequency, with drill-down options for detailed data. Pre-rendered hotspot visualizations further reduced loading times. While these

enhancements improved user experience, they risked oversimplification, highlighting the need for adaptive visualization strategies tailored to managers, engineers, and researchers.

Other limitations undermining the overall trustworthiness of this DT system are the reliability of low-cost sensors, the absence of a clear workflow with coding techniques for front-end and back-end integrations, and the lack of a calibration loop. Implementing low-cost sensors requires advanced skills in algorithm development, coding, and calibration to ensure the system's accuracy. Processing the large volume of real-time data also demands substantial hardware investment.

Conclusion and recommendation

In this paper, we presented a BIM-enhanced DT architecture tailored for pollution management in building renovation projects. The platform was designed for real-time environmental monitoring and regulatory responsiveness, thereby clarifying how to establish a BIM-based DT for renovating existing buildings. By defining minimum information requirements and aligning them with project objectives, we can resolve major uncertainties in the technical and practical implementation of BIM-based DTs, offering a pathway for more effective environmental and safety management in construction.

The proposed DT architecture was characterized by a semantically layered decomposition strategy. It was represented by five interdependent dimensions, namely, PEs, VMs, DD, Ss, and CNs. Each dimension contributes to the system's competence to support dynamic, data-driven decision-making in operationally sensitive contexts. The LOIN framework was leveraged to define as-needed BIM models, delineating baseline information structures necessary for dynamic pollution monitoring. This platform aligned LOIN and LOD with project objectives to optimize resource allocation, sensor placement, and project stakeholder engagement.

Future research should prioritize the adoption of semantic ontologies and IFC standards to enhance interoperability, support spatial reasoning, and enable automated hotspot identification. A key evolution involves expanding the current five-dimensional architecture into a CDT framework. This expansion requires integrating cognitive essentials as default components, such as a dedicated knowledge layer and reasoning engines, to enable the cognitive aspects of the DT.

Another promising direction is the advancement of cognitive DTs that move beyond monitoring to reasoning, predicting, and recommending mitigation strategies. AI-driven analytics, anomaly detection, adaptive rule engines, and automated workflows, such as dust suppression or schedule adjustments triggered by exceedances, can significantly improve responsiveness and efficiency. Other future research includes complaint management modules and participatory strategies to support user-driven feedback and adaptive responses. The integration of AI and camera systems can also extend the functionality of BIM-based DTs.

Author contributions

CRediT: **Truong-An Pham**: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Visualization, Writing – original draft; **Veerasak Likhitrungsilp**: Conceptualization, Methodology, Project administration, Resources, Supervision, Validation, Writing – review & editing.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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