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A Semantic-Enabled Common Data Environment for Real-Time Digital Twin Applications in Small-Scale Construction Projects

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Abstract

The integration of Building Information Modeling (BIM) and Digital Twin (DT) systems has reshaped construction project delivery, but their application remains concentrated in large, resource-intensive developments. Small-scale projects, which dominate the built environment in many regions, often lack access to advanced digital platforms due to financial constraints, insufficient infrastructure, and limited technical capacity. Existing Common Data Environment (CDE) frameworks are typically monolithic and costly, making them unsuitable for the flexible and affordable deployment needed in these contexts. A persistent barrier is semantic fragmentation: without interoperable data exchange across BIM, Internet of Things (IoT) devices, and Geographic Information Systems (GIS), project information remains siloed and underutilized. This study introduces a modular, semantic-enabled CDE architecture designed specifically for small-scale projects. The framework incorporates lightweight ontologies, microservices, and knowledge graphs to deliver scalable and semantically coherent integration of BIM–IoT–GIS datasets. To validate its applicability, the research applies the model to a three-storey educational building, demonstrating how real-time DT functionality can be achieved with minimal infrastructure demands. The case study highlights improvements in data exchange, operational monitoring, and sustainability analysis, showing how the architecture supports predictive maintenance and decision-making. By synthesizing insights from literature and practical demonstration, the paper proposes a blueprint for democratizing DT adoption, enabling affordable, adaptable, and interoperable solutions for small-scale construction projects.

Keywords: Digital Twin (DT); Building Information Modeling (BIM); Common Data Environment (CDE); Semantic Interoperability; Small-Scale Construction Projects.

1. Introduction

The integration of Building Information Modeling (BIM) and Digital Twin (DT) technologies is reshaping the delivery of construction projects by enabling data-driven decision-making, continuous real-time monitoring, and advanced simulation capabilities (see Figure 1). In large-scale developments, such as smart cities, transport hubs, and industrial complexes, these technologies are typically supported by robust Common Data Environment (CDE) platforms that consolidate heterogeneous datasets throughout the project lifecycle [1-3]. However, the benefits of such digital ecosystems have yet to be fully realized in small-scale construction projects, including residential buildings, community facilities, and small industrial assets, which often remain at the periphery of the digital transformation agenda [4, 5]. This imbalance underscores a persistent digital divide within the construction industry, where smaller projects risk being excluded from the adoption of advanced BIM-DT practices.

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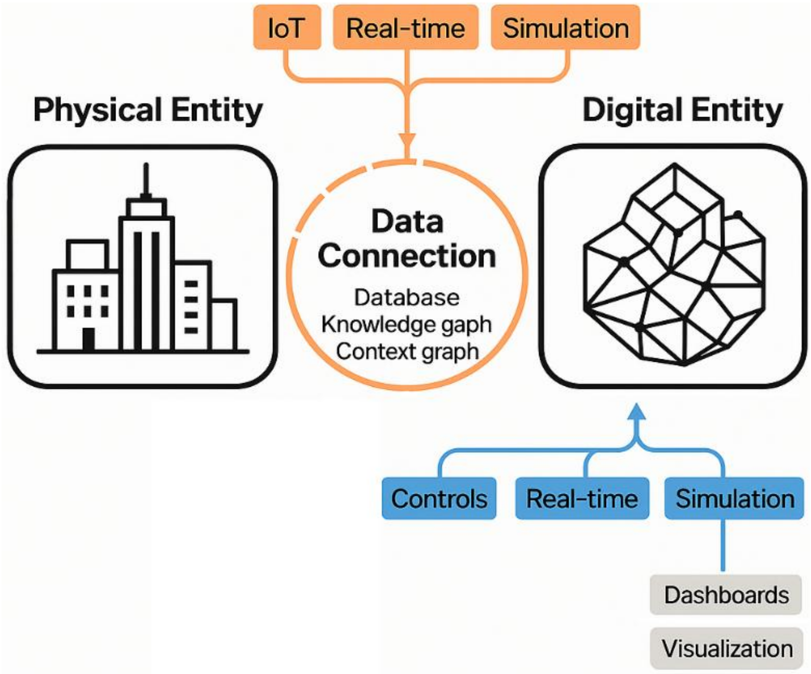

Figure 1. Illustrative representation of digital twin integration with physical assets and data flows [6-9]

More specifically, small-scale projects face numerous barriers to implementing BIM-DT solutions. Limited budgets, inadequate ICT infrastructure, and a shortage of skilled technical personnel hinder the deployment of sophisticated CDE platforms and real-time DT applications [10-12]. These challenges are particularly acute in developing countries, where weak institutional frameworks, high software licensing costs, and limited digital literacy further impede innovation [13]. Even modest attempts to adopt BIM or DT in such low-resource settings are often undermined by fragmented workflows and the absence of integration with Internet of Things (IoT) sensors or Geographic Information System (GIS) data, components essential for real-time, context-aware decision-making on site [5].

Beyond resource constraints, technological and data interoperability issues pose additional challenges. Existing CDE architectures could be monolithic and tightly coupled, lacking the flexibility, scalability, and cost efficiency required for smaller or short-term projects [3, 14]. Moreover, the absence of semantic interoperability means that data generated from BIM models, IoT devices, and GIS platforms can remain siloed, preventing seamless data exchange [6, 12]. This fragmentation limits the formation of a comprehensive digital representation of assets and constrains opportunities for downstream applications such as predictive maintenance, energy optimization, and sustainability assessment [15, 16]. While large-scale projects typically employ mature ontologies and standardized schemas to ensure semantic consistency and automated reasoning across datasets, small-scale projects seldom have access to such frameworks, leading to redundant data handling and inconsistent information management [17, 18].

To address these gaps, this study proposes a modular, semantically enabled CDE architecture specifically tailored for small-scale projects. The proposed framework utilizes lightweight ontologies to integrally combine BIM data with real-time IoT sensor streams and GIS information, enabling a unified digital twin representation without the need for heavy infrastructure. It supports real-time monitoring and control of project operations with minimal cost and technical overhead. The remainder of this paper is structured as follows: Section 2 reviews the related literature to clearly identify the research gaps; Section 3 presents the proposed framework; Section 4 describes a case study demonstrating its implementation; and Section 5 discusses the results and Conclusion part will conclude with key findings, limitation and future research directions.

2. Related Studies and State-of-the-Art Developments

2.1. Common Data Environment and BIM–Digital Twin Integration

Building Information Modeling (BIM) and Digital Twin (DT) are increasingly viewed as transformative for the design, delivery, and operation of built assets. Their integration, however, depends on effective data governance and information management strategies. The Common Data Environment has emerged as a central concept to address this requirement. As formalized in ISO 19650, a CDE establishes a collaborative workspace where project data is stored, versioned, and exchanged, ensuring that all stakeholders have access to an authoritative source of information. Its origins lie in responses to fragmented information flows and the absence of shared protocols, which earlier studies identified as drivers of inefficiencies and miscommunication in construction projects [19].

Despite the benefits of standardized coordination, traditional BIM-based CDEs are often limited by proprietary systems that restrict interoperability. Al-Sadoon et al. (2025) [20] highlight that existing frameworks are inadequate for complete BIM–DT integration because they tend to create siloed environments rather than fostering seamless integration. To overcome these constraints, researchers have proposed enhanced CDEs underpinned by semantic technologies. Steiner (2025) [21], for instance, presents a model where data sources, management components, and end users are systematically connected, while Stanton (2025) [22] emphasizes the value of real-time linkages between live sensor data and BIM models. Such designs position the CDE as the backbone of digital twin ecosystems, facilitating continuous data flows and feedback loops.

Beyond technology, governance considerations are vital. Questions of ownership, access rights, and data ethics are increasingly recognized as critical to sustainable CDE adoption. Ibrahim (2026) [23] warns that without transparent rules, conflicts over digital twin data use may arise. Parallel to these scholarly concerns, the European Commission has advanced the idea of a continent-wide “data space” to promote interoperability and stimulate innovation (European Commission, 2020a). Overall, a well-designed CDE provides the collaborative infrastructure necessary for integrating BIM models, IoT streams, and geospatial datasets. Yet, persistent obstacles such as absent global standards and inconsistent data schemas continue to limit true interoperability [20]. Current research agendas therefore focus on embedding semantic web principles and open data frameworks into the CDE concept, extending its capability to meet the demands of next-generation digital twins.

2.2. Digital Twins in Small-Scale Construction

Digital twins promise advantages not only for megaprojects but also for small-scale construction. Real-time monitoring, simulation, and predictive analytics can help SMEs improve decision-making, reduce rework, and manage costs more effectively. Case evidence demonstrates that integrating BIM models with live operational data can streamline maintenance processes and enhance performance monitoring, even for relatively simple assets. Waqar et al. (2023) [24] and Wang et al. (2024) [25] similarly argue that DT applications, if adapted to smaller projects, can accelerate delivery and raise overall quality.

Nonetheless, widespread adoption in SME contexts remains limited. The financial burden of implementing BIM and DT is consistently ranked as the most pressing barrier. High software costs, specialized hardware, and training requirements make these technologies less affordable for smaller contractors. European Commission (2025) [26] documents echo this finding, noting that upskilling expenditures add to the affordability gap. Compounding the issue is the shortage of digitally proficient staff.

Researchers classify these barriers into technical, organizational, and behavioral categories. Technical limitations include inadequate digital literacy and scarce IT infrastructure, such as limited access to cloud services or unreliable internet connections on small construction sites [5]. Organizational challenges stem from weak management support and unclear returns on investment, while cultural resistance to abandoning established practices further slows adoption [27]. In addition, many commercial BIM/DT tools are designed for large, complex projects and are ill-suited for modest undertakings. Waqar et al. (2023) [24] observe that existing modules rarely address the needs of small projects, creating a demand for lightweight, modular solutions that can be adapted to scale.

Despite these constraints, there is growing recognition that SMEs cannot ignore digital transformation. Governments and industry associations are beginning to address this imbalance. The European Commission has identified digitalization gaps among construction SMEs and has recommended targeted measures to bridge them [28]. Similarly, Alsakka et al. (2024) [8] argue that integrating DTs into small-scale or offsite construction is essential for competitiveness in the era of Construction 4.0. The literature suggests that effective responses will require a combination of financial incentives, development of cost-efficient, modular DT platforms, and structured capacity-building programs. Such measures would allow SMEs to access benefits already realized in large-scale BIM–DT implementations.

2.3. Semantic Web and Ontologies in the AECO Sector

Achieving interoperability across BIM, DT, IoT, and GIS domains has proven difficult through traditional data models alone. To overcome this, the Architecture, Engineering, Construction, and Operations (AECO) sector has increasingly adopted semantic web technologies. These approaches employ ontologies to formalize concepts and relationships, thereby enabling machine-readable integration of heterogeneous datasets. Ontologies such as the Building Topology Ontology (BOT), Brick Schema, and IfcOWL illustrate this movement (see Figure 2). BOT provides a lightweight vocabulary for describing building spaces, Brick offers granular semantics for HVAC and sensor networks, and IfcOWL enables IFC-based models to be expressed in RDF for semantic querying [17, 27, 29]. Research shows that these ontologies support cross-domain reasoning and allow BIM data to be enriched with sensor and geospatial inputs, creating robust semantic digital twins [30]. This integration allows advanced queries and automated compliance checking. For example, a manager could identify all building components associated with sensors reporting anomalies, or verify code compliance against rule-based ontological models [24].

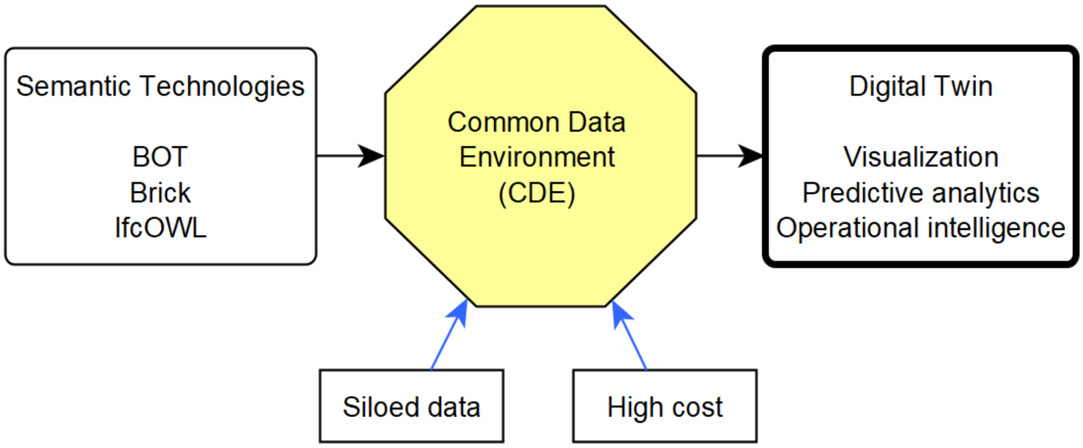

Figure 2. Integration of Semantic Technologies and CDE for Digital Twin Development

However, challenges remain. Developing and mapping ontologies is complex and resource-intensive, requiring both domain expertise and consensus on standards [31]. Performance limitations, particularly with large graph databases, and the limited familiarity of practitioners with semantic technologies also inhibit adoption. Privacy and security concerns emerge when linking sensitive building data with operational datasets. Despite these obstacles, initiatives such as the W3C Linked Building Data group and EU-funded programs like BIM2TWIN are advancing shared semantic frameworks, indicating a long-term trend toward ontology-driven CDEs and digital twins.

2.4. Research Projects and Remaining Gaps

Several European projects have pioneered efforts to integrate BIM and DT at scale. COGITO focused on AI-enhanced DT platforms, BIM2TWIN promoted ontology-driven decision support, and ASHVIN integrated sensors for real-time control [28, 32, 33]. These initiatives have expanded understanding of federated architectures, data sovereignty, and simulation-based analytics. Nevertheless, significant gaps remain. Most existing platforms have been designed for large, resource-rich contexts, leaving questions of scalability to SMEs unresolved [21]. Smaller contractors often lack the infrastructure, both technical and organizational, to adopt heavy cloud-based or sensor-intensive systems. Moshood et al. (2024) [30] emphasize the need for incremental, modular solutions that can be phased into practice. Equally pressing is the lack of universally adopted data standards. The absence of common ontologies and schemas perpetuates data silos, undermining efforts to merge BIM, IoT, and GIS [20].

Data reliability is another critical issue. Without robust validation and updating processes, CDEs risk hosting outdated or inconsistent information. The European Commission's Digital Building Logbook initiative highlights the importance of lifecycle documentation, yet its practical application in smaller projects is still underdeveloped [33]. Finally, economic feasibility remains a decisive barrier: adoption will lag until clear cost–benefit evidence is available [4, 27].

Across the reviewed literature, a consistent gap emerges: while semantic-based and real-time integrated Digital Twin frameworks are evolving, their complexity and cost remain prohibitive for small-scale applications. There is a lack of modular, low-cost, ontology-enabled CDE systems that can support real-time operations in such contexts. This underscores the need for "lightweight semantic CDE" solutions designed to address the unique constraints and opportunities in smaller built assets.

3. Methodological Framework and Research Approach

This study employs a conceptual modeling approach based on secondary data, including peer-reviewed articles, technical reports, and open-source ontologies, to develop a lightweight semantic-enabled CDE for small-scale construction projects integrating BIM and Digital Twin (DT) technologies.

The process comprises five stages. First, existing CDE architectures were analyzed to identify that centralized and federated models dominate large-scale projects, offering robust data exchange but at high cost and complexity, and cloud-based CDEs provide flexibility but still face interoperability challenges when integrating IoT, GIS, and BIM data. After CDE architectures were analyzed, essential data layers for DT in small buildings were identified: (i) 3D geometry and spatial relationships (IFC/BOT), (ii) environmental sensor data, (iii) geospatial references, and (iv) temporal operation data for analytics. The semantic layer was then designed using BOT, Brick Schema, and IfcOWL. BOT models spatial hierarchies, Brick supports sensor-system integration, and IfcOWL aligns IFC-based BIM data. These are modeled in RDF/OWL with SPARQL endpoints for querying.

Based on analysis, a modular data pipeline was designed, comprising (1) acquisition via IoT/BIM tools, (2) semantic mapping and data fusion, and (3) real-time visualization. Modularity was applied to ensure adaptability in low-resource contexts [34]. Finally, a case study of a small educational facility with limited budget and infrastructure tests deployment, latency, and ontology usability, demonstrating the feasibility of real-time semantic interoperability.

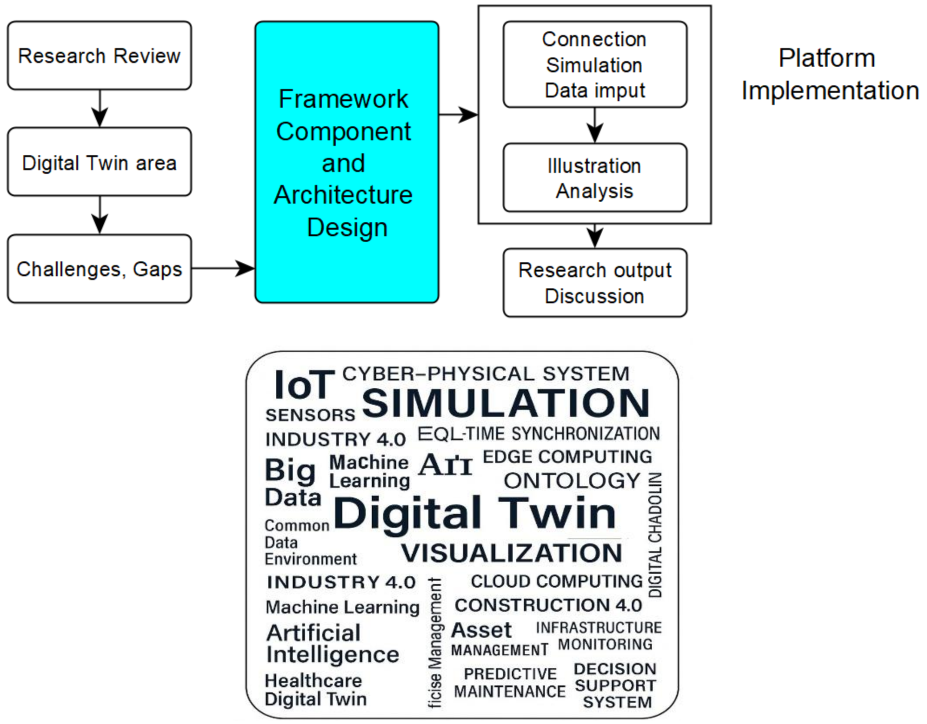

Figure 3. Research flowchart and keyword search implemented in this study for framework development

4. Proposed Semantic-Enabled CDE Architecture

4.1. Overview of System Architecture

The proposed CDE integrates BIM, IoT, and GIS data via semantic web technologies in a multi-layer structure, aligning with digital twin frameworks that separate acquisition, integration, modeling, and service layers. Figure 4 illustrates the semantic-enabled CDE's key layers and their functional roles.

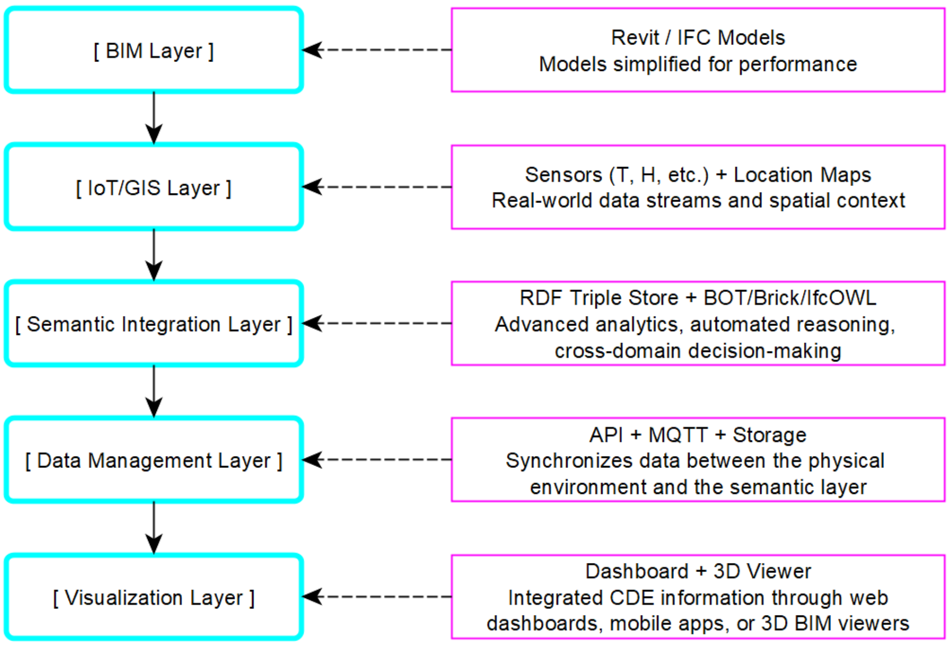

Figure 4. Proposed Architecture for Semantic-Enabled CDE for Digital Twin Applications in Small-Scale Construction Projects

- **BIM Layer (Design Data):** The BIM Layer contains static design data, including 3D geometry and metadata from BIM models (e.g., IFC, Revit). It serves as the authoritative source for building elements, spatial hierarchy, and a single source of truth. Standards like IFC can be transformed into semantic formats (ifcOWL, BOT) for integration. Initiatives such as Linked Building Data provide ontologies to represent spaces and elements. Architectural, structural, and MEP data are prepared for linkage with real-time inputs. Large models may be simplified for performance; for example, a 500 MB Revit file was reduced to 20 MB by retaining only essential spatial and monitoring information, improving runtime efficiency. This layer ensures accurate virtual representation and facilitates seamless integration with higher layers in the semantic-enabled CDE.

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- **The IoT/GIS Layer:** This layer captures dynamic real-world data streams and spatial context. It integrates IoT sensors (e.g., temperature, humidity, light) with GIS-based location data (coordinates, floor plans, maps). Sensors enable real-time monitoring, reducing manual data collection, and connect via networks (Wi-Fi, BLE) through middleware or gateways. Geospatial inputs situate readings within physical space, allowing sensor data to be visualized on maps or 3D BIM models. This integration removes data silos, enhancing decision-making. For example, environmental or wearable sensors can stream real-time conditions or equipment status, which, when combined with BIM and displayed on a GIS interface, reveal resource utilization patterns. In the proposed architecture, this layer performs all physical data acquisition, both sensor telemetry and spatial positioning, aligning with the “data acquisition” stage of digital twin frameworks.

- **Semantic Integration Layer (Knowledge Graph):** The Semantic Integration Layer unifies BIM, IoT, and GIS data in a knowledge graph managed by an RDF triple store or graph database, enabling semantic queries across domains. Ontologies define the schema: the Building Topology Ontology (BOT) models spatial hierarchies (sites, buildings, storeys, rooms), while the Brick schema defines sensors, equipment, and their links to spaces for sensor observations. Mapping BIM elements and IoT readings to these ontology classes creates a common data model where, for example, a temperature sensor *is located in* a specific room. Standards ensure consistent meaning and interoperability across heterogeneous data. Knowledge graphs are well suited for digital twins, flexibly integrating multi-domain datasets and supporting context-rich queries. In this architecture, a triple store holds BIM geometry, IoT metadata, and geospatial context, connected via microservices. This layer mediates between static BIM design data and real-time telemetry, linking them through unique identifiers and semantic relationships. Functioning as the “data/model integration” stage in digital twin frameworks, it semantically maps disparate sources into a cohesive, queryable structure that supports advanced analytics, automated reasoning, and cross-domain decision-making in small-scale construction projects.

- **Data Management Layer (Processing and Storage):** The Data Management Layer ingests, processes, and synchronizes data between the physical environment and the semantic layer. It incorporates databases, pipelines, and middleware to handle real-time updates from diverse sources. IoT sensor data is typically collected via platforms or message brokers, then streamed through tools for preprocessing before integration. Lightweight protocols enable secure data transfer to the CDE. Functions include cleaning, normalization, and historical storage, often using NoSQL or time-series databases for structured and semi-structured data. Middleware ensures efficient routing, while transformation services convert raw values into semantic triples aligned with the knowledge graph. Synchronization mechanisms update both live sensor data and periodic BIM or external data changes, ensuring semantic coherence. By capturing readings (e.g., temperature every minute), standardizing units, and flagging anomalies before injecting them into the knowledge graph, this layer ensures minimal latency and consistent integration. Ultimately, it serves as the operational backbone linking physical devices with the semantic-enabled CDE, enabling timely, accurate, and context-rich digital twin updates for small-scale construction projects.

- **Visualization Layer:** The Visualization Layer comprises user-facing applications that present integrated CDE information through web dashboards, mobile apps, or 3D BIM viewers. These tools combine static building models with live sensor data for intuitive understanding. Prior research emphasizes offering multiple interfaces – from 2D charts to immersive 3D environments – to meet diverse stakeholder needs. In our architecture, a web dashboard provides real-time graphs, trend analyses, and alerts (e.g., temperature history or threshold exceedance notifications). A 3D model viewer, built on platforms or game engines, enables virtual navigation of the building and spatial visualization of sensor readings (e.g., rooms color-coded by temperature). Back-end analytics feed processed results to the frontend: abnormal conditions can trigger alerts and highlight affected areas. This layer, akin to the "service" or "interaction" layer in other frameworks, ensures that facility managers, owners, and construction teams can monitor and manage assets effectively. Because the CDE is semantic-enabled, end-user applications can query the knowledge graph for tailored visualizations or reports. By merging analytical dashboards with spatial context, the Visualization Layer closes the loop from data acquisition to actionable insights, enhancing situational awareness and decision-making in small-scale construction projects.

4.2. Semantic Mapping Process

A cornerstone of the semantic-enabled CDE is the mapping of BIM and IoT data to a shared ontology framework, enabling integration at the data level. This involves translating entities from BIM and IoT domains into RDF triples that instantiate concepts from ontologies like BOT (for building topology) and Brick (for building sensors and systems). By doing so, both static building elements and dynamic sensor readings coexist in the same semantic graph, linked by meaningful relationships (see Figure 5).

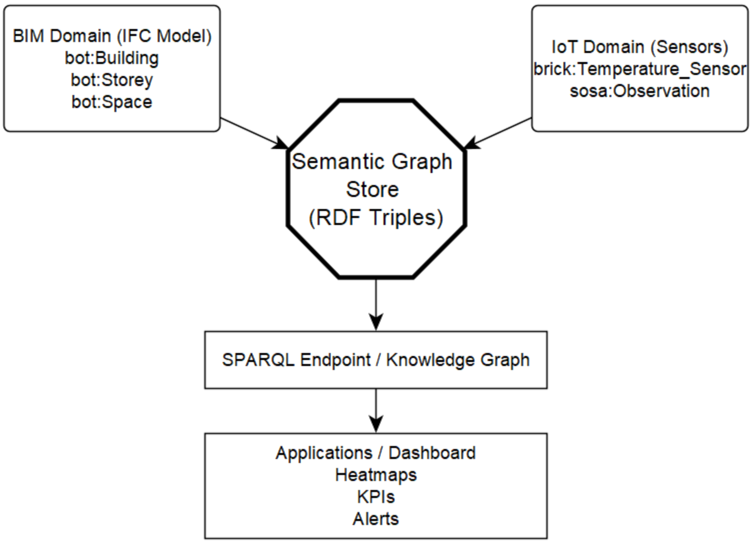


Figure 5. Semantic Mapping Process for Data Integration and Interoperability

Ontology Selection and Alignment: The W3C Linked Building Data ontologies are used for building structure, and the Brick schema for IoT devices and observations. BOT provides classes and properties to represent the hierarchy of a building and relationships like bot:hasSpace. Brick defines a taxonomy of building systems and sensors and their relationships, leveraging for sensor observations. BIM data is aligned with BOT, IoT data with Brick/SSN, and links between them established-often. Once mapped, triples are stored in a graph store for uniform querying.

Mapping BIM to Ontologies: BIM models (often in IFC) contain building elements and spaces. Data can be converted to RDF via ifcOWL or, more lightly, BOT and related ontologies. IFC Spatial Structure Elements become bot:Building, bot:Storey, bot:Space, with relationships preserved. Building elements can be mapped to the Building Element Ontology or Product ontology. Export can be automated or via API queries, preserving key identifiers like GUIDs for linking with IoT data.

Mapping IoT Data to Ontologies: Each IoT sensor is represented as a Brick class instance, e.g., brick:Temperature_Sensor. Measurements are modeled as sosa:Observation linked to the sensor. Sensors are linked to BIM context via brick:hasLocation or similar. Metadata or naming conventions in BIM and IoT systems can aid this mapping.

Data Import and Automation: Mapping can be automated through adapters or microservices. For BIM, an IFC-to-RDF converter reads files and generates triples. For IoT, a service subscribes to sensor data (e.g., via MQTT) and updates triples for observations. In some implementations, BIM IfcSensor entities with GUIDs are registered in IoT middleware with the same GUID, ensuring one-to-one correspondence. Queries to the knowledge graph can then treat BIM and IoT data as one dataset. Consistency in units and data types is maintained using RDF data types and Brick's unit definitions.

Integration Benefits: The semantic mapping links BIM→BOT (spaces, elements) and IoT→Brick (sensors, points), creating BOT–Brick relationships. This allows unified SPARQL queries, e.g., "List all rooms on Floor 1 with a temperature above 25°C, showing readings and sensor IDs." Such queries leverage both BIM (room/floor context) and IoT (live data) in one step.

4.3. Data Pipelines

With the architecture and mappings in place, the system operates through a data pipeline that moves information from raw source to actionable visualization in a continuous loop. The pipeline can be described in four main stages: (1) Data Collection, (2) Data Processing/Normalization, (3) Semantic Mapping & Integration, (4) Data Query & Visualization. This sequence ensures that data from the physical environment is captured, transformed into a unified semantic model, and then utilized by applications in real time. Each stage and the enabling technologies are described in Figure 6.

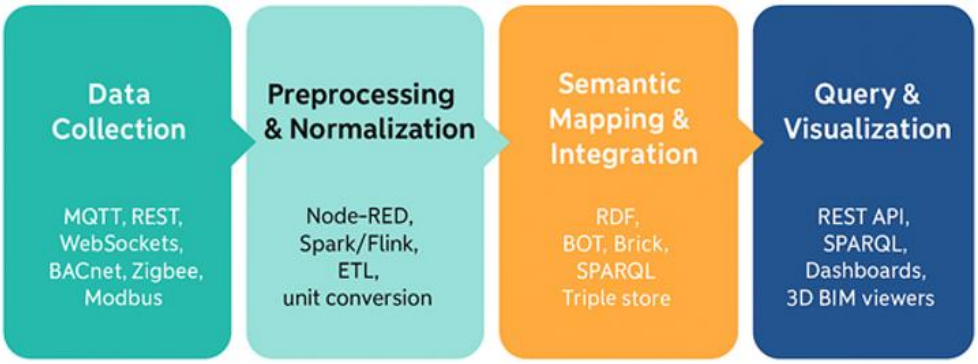


Figure 6. Real-time data pipeline for semantic-enabled CDE

Data Collection (Ingestion Stage): In the first stage, heterogeneous data from multiple sources are collected and streamed into the CDE, including IoT sensor measurements, external feeds, and manual inputs. IoT devices in the building publish telemetry at regular intervals via gateways or brokers using protocols or building automation standards. In our setup, an MQTT broker aggregates streams from building sensors, with topics structured by location (e.g., building1/floor1/room101/temperature). GIS data may also be integrated, either as a one-time import of building coordinates or as continuous tracking of moving assets. All incoming data are timestamped and forwarded to the processing layer. Middleware and edge devices can perform minor preprocessing before sending data to the cloud via MQTT or REST APIs. For high-throughput environments, platforms like Apache Kafka can buffer and distribute streams. The key requirements at this stage are secure, reliable transmission and minimal latency. This collection stage establishes the real-time acquisition pipeline, ensuring live sensor and contextual data flow continuously into the CDE to support timely processing, integration, and visualization within the digital twin environment.

Data Processing & Normalization: Once collected, data is preprocessed and normalized before integration. Raw sensor readings may be noisy, incomplete, or inconsistent, so the system filters, cleans, and transforms them. Steps include removing outliers, filling missing values, converting units to a common standard, and aligning timestamps for synchronization. Large BIM models may also be lightweighted by trimming to essential elements for faster queries. Processing can be handled by stream processors or ETL pipelines. Tools manage heavier analytics in batch or micro-batch mode, while Node-RED or custom scripts handle on-the-fly transformations. For example, sensor data might be averaged to one-minute intervals, smoothed to reduce noise, or validated before storage. Normalization also structures data according to the ontology schema, preparing identifiers and metadata for RDF triple insertion. A temperature reading such as "room=101, value=25.3, time=10:00" would be tagged with the corresponding sensor URI, typed as an xsd:float, and annotated with units (°C). Derived metrics or anomaly flags can also be computed at this stage. The result is a stream of clean, standardized sensor data and a filtered BIM dataset, both conforming to expected formats and ready for semantic ingestion into the knowledge graph.

Semantic Mapping & Integration (Transformation Stage): In this stage, processed data is transformed into RDF triples and inserted into the knowledge graph. If the BIM model is not yet loaded, it is imported into the triple store to establish building entities and relationships. Each new sensor observation is then semantically mapped according to the ontology alignment described in Section 4.2. The sensor is linked to its location with a statement. This process is typically managed by an IoT data adapter microservice that listens to a message broker and performs SPARQL Updates or API calls to insert triples.

In case of high-volume scenarios (hundreds of sensors), the system can batch readings into single transactions or apply streaming graph updates for efficiency. This maintains near real-time synchronization of the knowledge graph with live sensor data contextualized within BIM.

Defining this pipeline explicitly ensures consistency and scalability. New data sources or external systems can be integrated without disrupting the model's structure. Once data is in the graph, optional reasoning or analytics may be applied, such as inferring higher-level states, validating rules, or triggering alerts, but these are separate from the core integration pipeline.

By continuously merging live sensor streams with BIM context in RDF, the semantic integration stage keeps the digital twin's knowledge graph current, enabling accurate, context-rich queries and supporting informed decision-making across the building's lifecycle.

Data Query & Visualization (Delivery Stage): The final pipeline stage delivers actionable information to end-users and applications. With the CDE's knowledge graph populated with fused BIM and IoT data, access is provided via two main methods: API calls and direct queries.

Advanced users or analytics services can query the triple store directly (SPARQL for RDF stores, Cypher for property graphs) for complex joins or integrated data analysis. For instance, a SPARQL query could return the latest temperature for each room on Floor 1, ordered by value. Demonstrations showed retrieval of linked BIM, IoT, and process data in a single semantic query.

Once retrieved, data is visualized. The dashboard refreshes charts and status indicators in real time, either via subscriptions or polling the API. A 3D BIM viewer, such as Autodesk Forge, can overlay live sensor data on model elements, updating colors or tooltips as readings change. The system can trigger alerts when thresholds are exceeded, using rule engines or data analysis, and display notifications for abnormal patterns. Predictive analytics, such as forecasting a temperature rise within the next hour, can also be integrated into the dashboard.

The pipeline is cyclical: user actions generate new data that re-enters the pipeline. Historical data is logged for analysis, with old triples archived or time-series data compressed to maintain performance. Time-series databases work alongside the triple store to support both historical and real-time queries. This integrated delivery layer ensures that stakeholders, from facility managers to automated control systems, can access timely, contextualized insights, while maintaining a flexible architecture for future tools and data sources.

A timely, normalized, and context-rich flow of data from sensors to stakeholders is delivered through the proposed semantic-enabled CDE pipeline. Automated collection is first performed, after which cleaning and organization are carried out using stream processing and ETL tools. The data is then semantically integrated into a knowledge graph through RDF and ontology mapping, before being disseminated via APIs and dashboards using REST or SPARQL queries. Real-time monitoring, predictive analytics, automated control, and facility optimization are enabled by key technologies such as MQTT, REST, SPARQL, and RDF. By having each stage from collection to display explicitly defined, the CDE is maintained as a live, authoritative hub, capable of supporting scalable and iterative data management as new sources are introduced.

5. Applied Case Study: Demonstrating the Proposed Framework

A three-story school building was selected as a representative case to demonstrate the deployment of the proposed Digital Twin (DT) framework. The building consists of standard classrooms and corridors, typical of educational environments where operational management and environmental monitoring are critical. Although only a small set of IoT devices, measuring temperature and humidity, were installed in selected classrooms, these sensors successfully transmitted data via Bluetooth Low Energy (BLE) to a local gateway, which subsequently relayed information to a cloud-based database. This setup ensured a continuous, albeit spatially constrained, real-time data stream reflecting the indoor environmental dynamics of the building.

To address the limited spatial coverage of physical sensors, additional data were integrated from simulations and secondary sources. Historical weather records from a local database, occupancy schedules, and internal heat-gain profiles based on national building standards were employed to generate synthetic data for unsensed areas. This fusion of real and simulated data produced a hybrid dataset, enhancing the completeness and reliability of the DT representation. Such hybridization follows established practices in early-stage DT research, where sparse empirical data are supplemented with modeled information to emulate dense instrumentation [30, 35]. The calibrated dataset provided a more holistic reflection of the building's performance, supporting both diagnostic and predictive analytics.

The DT platform was developed as a multi-layer system comprising physical, virtual, and application layers. The physical layer collected field data through uniquely identified IoT sensors linked to spatial coordinates within the building. The virtual layer, modeled in Autodesk Revit, represented the BIM environment reduced from approximately 500 MB to 20 MB by retaining only essential geometric and attribute data necessary for monitoring. Each spatial entity was assigned a consistent identifier, enabling real-time association with its corresponding sensor or simulation data. This configuration allowed users to click on a room in the BIM interface and instantly visualize real-time readings, historical trends, or anomalies through a web-based dashboard. The Semantic Mapping Process and Data Pipelines, explicitly defined within the framework, ensured that raw sensor streams were automatically aligned with ontology terms and delivered through structured, interoperable channels. This enabled smooth data exchange, real-time synchronization, and integration with predictive models (see Figures 7 and 8).

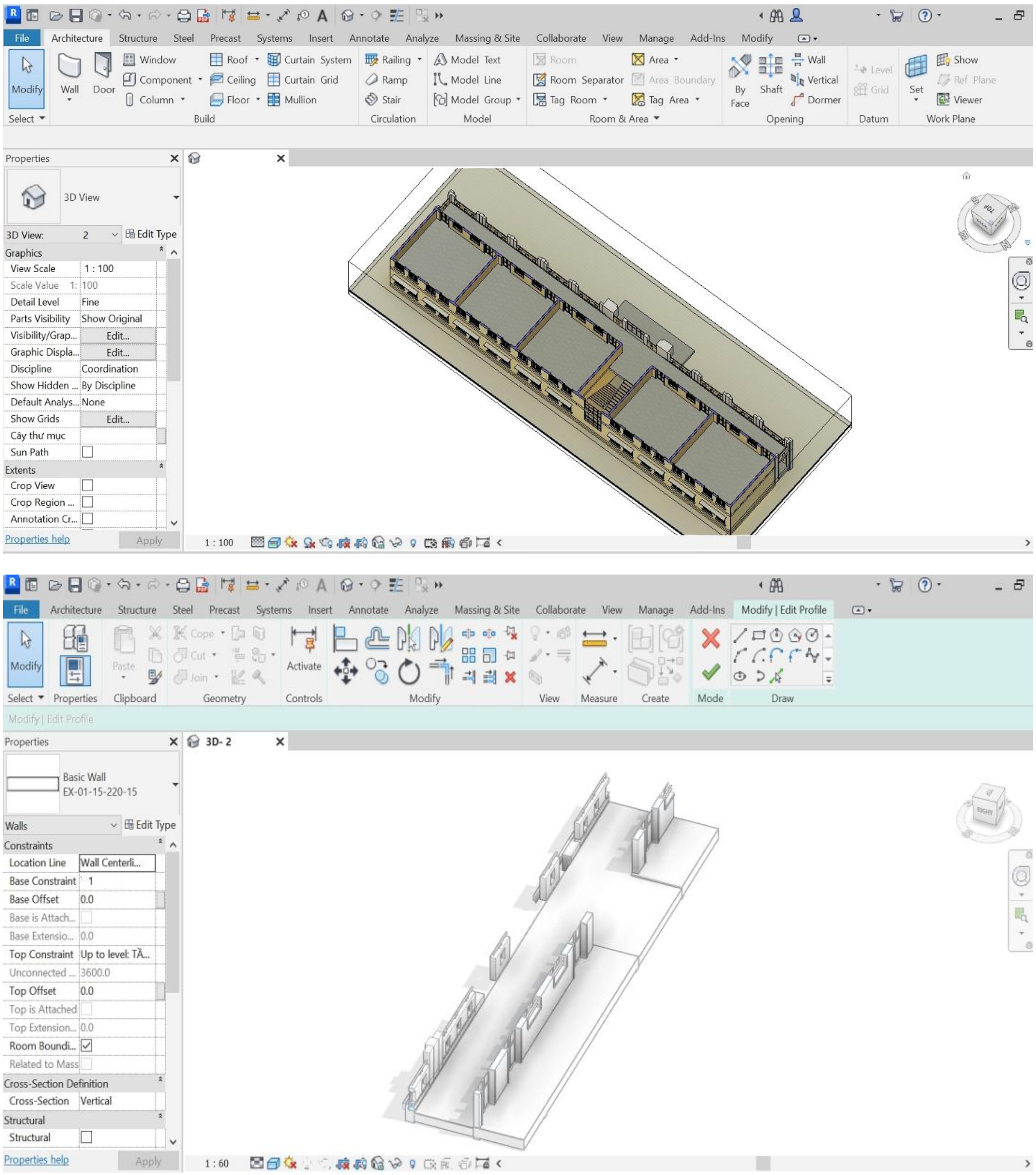
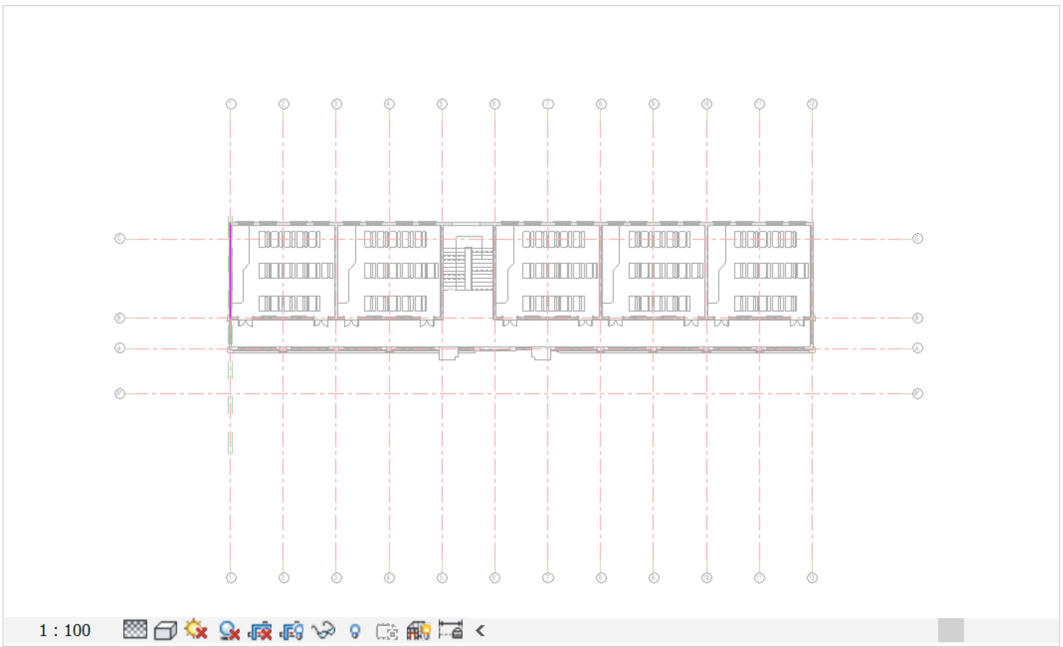


Figure 7. The 3D representation of the case study building's second floor



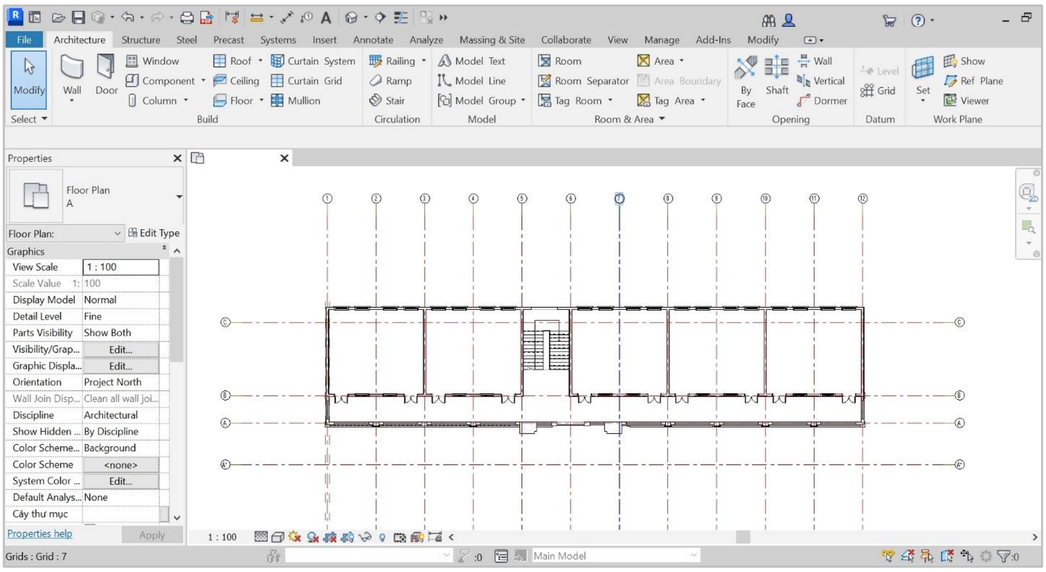


Figure 8. Simplified layout of the second-floor rooms

The overall system adhered to a classical DT paradigm, maintaining a live connection between physical assets, data pipelines, and virtual representations. The DT server hosted analytics and simulation modules, while the dashboard provided intuitive visualization and user interaction (Figure 9). Communication among system components employed standard web protocols, ensuring modularity and cross-platform interoperability. This design achieved near-real-time synchronization, a critical feature for effective DT implementation [11, 36].

Given the sparse sensor deployment, simulated and secondary data streams were indispensable for achieving full coverage. Real sensor readings served as calibration references to fine-tune simulated results, ensuring data fidelity across unsensed zones. A simplified building energy model was developed to simulate thermal comfort under typical occupancy and climatic conditions, supplemented with benchmark data for indoor air quality and HVAC operation in educational facilities. Consequently, the DT achieved the functionality of a "virtually instrumented" system, where simulated inputs reinforced the limited sensor network. Previous studies corroborate the feasibility and scientific rigor of this hybridized data strategy for early-stage DT applications [7, 8, 37].

The implemented DT facilitated continuous environmental monitoring and operational insight. Real-time data streaming every few minutes allowed facility managers to visualize temperature and humidity conditions across all classrooms. Deviations were immediately identifiable, with one overheating classroom traced to a blocked ventilation duct, demonstrating the DT's capacity for diagnostic analysis. Predictive analytics further extended system functionality. A Long Short-Term Memory (LSTM) neural network trained on the hybrid dataset achieved a normalized root-mean-square error (NRMSE) of 3–5% for short-term temperature and humidity forecasts, matching or exceeding performance reported in comparable DT-based forecasting studies. Moreover, the predictive module enabled intelligent anomaly detection: when measured values diverged significantly from predicted trends, automatic alerts were triggered. For instance, one classroom predicted to remain at 24 °C recorded an actual temperature of 27 °C, leading to a prompt inspection that revealed a heating system malfunction. The quantitative results are presented for the rooms identified by the codes illustrated in Figure 10, whereas Figure 11 depicts the weekly load profile heatmap, showing variations in power demand (kW) across hours of the day.

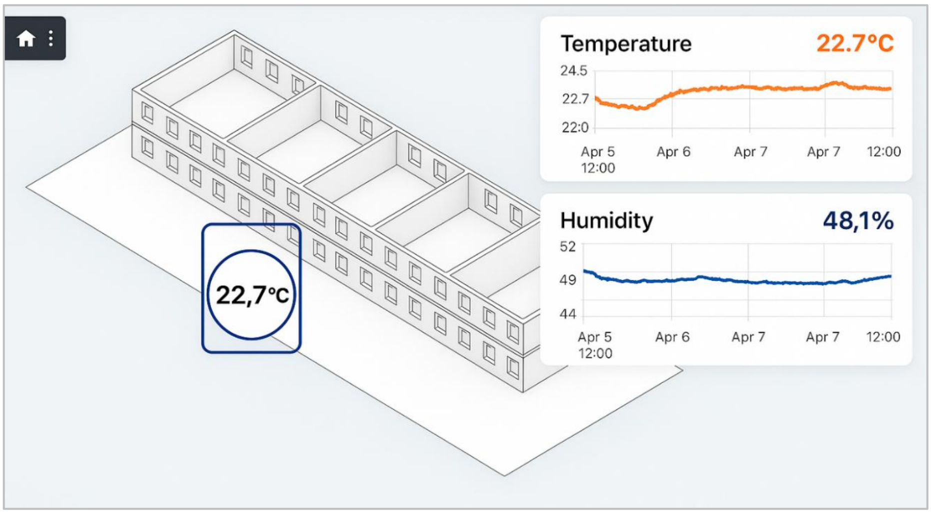


Figure 9. Demonstration of Digital Twin Dashboard for Real-Time Indoor Environment Monitoring

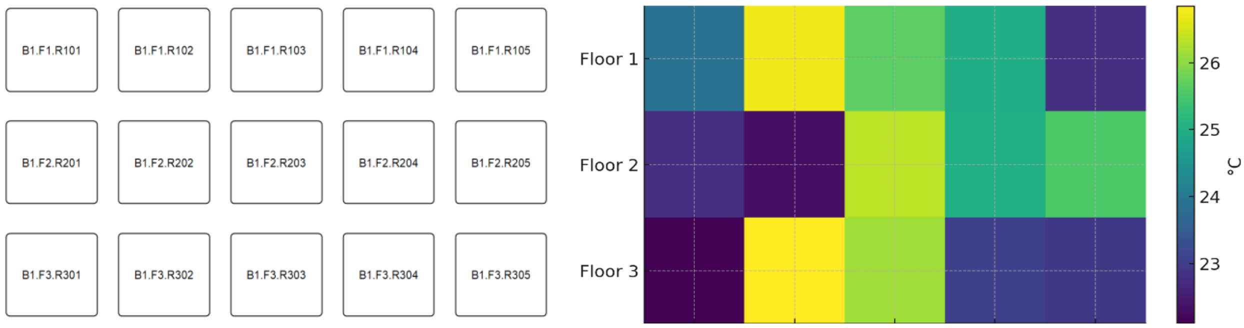


Figure 10. Demonstration of rooms with space codes and temperature distribution across building floors

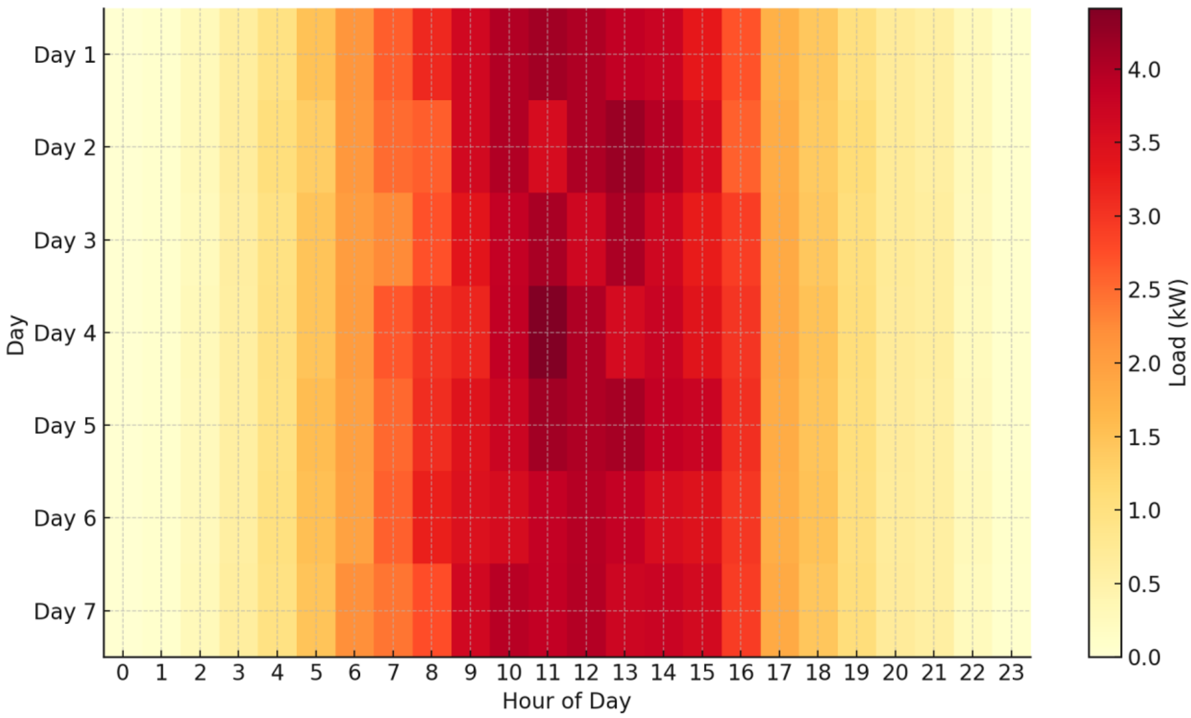


Figure 11. Weekly Load Profile Heatmap (kW) by Hour of Day

Overall, the case study validates that the proposed semantic-enabled CDE and DT framework can operate in low-infrastructure environments. By combining limited sensor inputs with simulated data, the system achieved live synchronization, intuitive visualization, and predictive intelligence, offering a scalable and affordable pathway for DT adoption in small-scale construction projects.

6. Analysis and Discussion of Research Results

6.1. Advantages of the Proposed Model

The proposed semantic-enabled Common Data Environment (CDE) architecture demonstrates several advantages that directly address the limitations identified in previous studies on small-scale Building Information Modeling (BIM) and Digital Twin (DT) applications.

First, its modular system design simplifies deployment, operation, and maintenance by dividing the system into loosely coupled services and data repositories. This architecture allows individual components to be updated or replaced independently, avoiding costly full-system reconfigurations. Such a plug-in approach aligns with the modular development principles highlighted by Schlenger et al. (2025) [29] and Shehata et al. (2025) [27], who found that modular Digital Twin systems enhance flexibility and reduce lifecycle costs. Compared to traditional monolithic CDEs, the proposed framework enables incremental scaling, allowing small projects to begin with essential functions and progressively integrate advanced capabilities as resources permit. This not only improves maintainability but also minimizes the risk of cascading failures by isolating technical issues within individual modules.

A second major strength lies in the semantic data structuring and ontology-based integration. By employing Resource Description Framework (RDF) graphs and domain ontologies, the framework provides explicit, machine-readable definitions of entities and relationships, ensuring interoperability across platforms and project phases. Earlier research emphasized that ontology-driven models enhance the consistency and reusability of construction data [38], while supporting cross-domain reasoning for operational decision-making [39]. The present results corroborate these findings: the semantic CDE effectively unifies heterogeneous data types, such as BIM models, IoT sensor streams, and tabular datasets, allowing seamless integration under limited budgets. Compared with previous CDE implementations, which often relied on proprietary data formats, the proposed approach achieves greater transparency and portability, extending data value beyond a single project lifecycle.

Finally, the cost-effectiveness of the proposed solution marks a practical advancement over earlier DT prototypes that required significant software investment and vendor-specific infrastructure [5, 40]. By utilizing open-source tools and open data standards, the proposed CDE removes common barriers related to licensing, training, and cloud infrastructure costs. This outcome aligns with the experience of prior low-cost DT initiatives, such as university campus monitoring systems that successfully achieved BIM–IoT integration using open frameworks. The present study reinforces that open, modular architectures can deliver reliable performance while remaining financially accessible to small organizations and community projects.

6.2. Remaining Challenges

Despite its demonstrated potential, several challenges persist. A primary barrier concerns the limited availability of ontology-literate professionals in the Architecture, Engineering, and Construction (AEC) sector. As Kosse et al. (2025) [41] note, semantic technologies such as RDF, OWL, and SPARQL remain underutilized due to steep learning curves and a lack of domain-specific training. Small firms, often operating with minimal staff and constrained budgets [4], rarely possess the expertise required for developing and maintaining ontological structures. Without accessible tools and user-friendly interfaces, the benefits of semantic modeling may remain confined to research-oriented settings. The findings therefore suggest that developing simplified ontology editors and embedding training modules within BIM software would significantly lower the adoption threshold.

Another limitation involves real-time data pipeline reliability. As reported by Yan et al. (2025b) [40], synchronizing heterogeneous sensor inputs with semantic BIM representations remains technically demanding, particularly under constrained bandwidth or low-cost hardware conditions. The current implementation encountered similar issues: mismatches in data granularity and streaming frequency occasionally produced latency and temporary inconsistencies. These findings are consistent with Lei et al. (2023) [36], who emphasized the need for resilient middleware to manage asynchronous data flows. Future iterations of the proposed framework should incorporate advanced buffering, validation, and temporal alignment mechanisms to maintain integrity within the knowledge graph during high-frequency updates.

Besides, data security and access control continue to pose critical concerns. As highlighted by Lindholm et al. (2015) [10], CDEs may store sensitive architectural and operational information that, if compromised, could endanger both safety and privacy. The present results confirm the necessity of implementing multi-layered protection, including role-based authorization, encrypted transmission, and blockchain-backed audit trails. Strengthening these safeguards would enhance stakeholder confidence, particularly for cloud-hosted or multi-party DT systems.

Intermittent connectivity is also another possible challenge. The proposed framework is optimized for low-resource environments and can tolerate intermittent connectivity through localized data handling and synchronization mechanisms. In regions where internet access is unstable, the CDE can operate in a hybrid configuration: critical components run on a local server or edge device to maintain real-time monitoring and data logging even during network outages. The system temporarily stores sensor readings locally, via an MQTT broker or gateway, and synchronizes them with the cloud repository once connectivity is restored, using a store-and-forward strategy to ensure eventual consistency. This design allows on-site users to access the CDE and sustain automated processes offline, while unique timestamps and ID tracking prevent data loss or duplication during reconnection. Consequently, the framework supports continuous digital-twin operations in developing regions where reliable connectivity cannot be guaranteed.

Finally, federating multiple small-project CDE into a shared regional or municipal digital ecosystem would introduce several critical challenges. The foremost concern is achieving data standardization and semantic interoperability, as projects often rely on distinct ontologies, schemas, and metadata conventions. Without harmonized standards, integration may result in inconsistent semantics and fragmented data silos. Equally important are governance and access control, requiring clear policies on data ownership, authorization, and privacy management. Technically, a federated CDE implies a distributed architecture where executing cross-domain queries and maintaining synchronization among heterogeneous knowledge graphs is complex and resource intensive. Scalability and reliability further constrain such systems, given the exponential growth in data volume and user activity at regional scales. Additionally, stakeholder coordination remains difficult since small projects are typically managed by separate organizations; achieving compliance with a unified semantic and governance framework demands strong institutional leadership and long-term collaboration.

6.3. Application Potential

The architecture's combination of modularity, semantic integration, and affordability suits various community-scale projects needing multi-stakeholder collaboration.

- **Social housing projects**: Housing organizations can integrate BIM models with operational data to improve efficiency and resident comfort. Repetitive units and standardized components make these ideal for data reuse. A semantic CDE could link asset lifecycles, maintenance logs, and energy use across portfolios, supporting preventative maintenance and sustainability goals. Case studies show early BIM adoption in public housing reduces waste and improves coordination. Semantic integration can also connect housing data to municipal GIS or energy systems for broader smart city integration.
- **Small public facilities**: Assets like pumping stations, substations, or heating plants, often unmanned and maintained by small teams, can be monitored remotely via the CDE. Integrating IoT feeds with BIM models enables live **equipment** tracking and predictive maintenance. Microservice-based knowledge graph systems have been applied successfully to varied infrastructure [39], proving feasibility. A semantic model ensures data is context-aware and aggregate-ready, allowing cities to network multiple small facilities' twins for optimized operations.
- **Educational buildings**: Schools and **universities** can use the CDE to integrate BIM with occupancy, air quality, temperature, and energy sensors. This supports comfort optimization and proactive maintenance. Open-source tools keep costs low, and semantic modelling captures relationships valuable for campus management. CDE use in academic buildings also improves coordination during renovations through up-to-date, shared records.
- **Community centres and civic buildings**: Facilities like libraries, clinics, and recreation centres often face irregular usage patterns. A semantic-enabled DT can correlate occupancy, energy, and HVAC data to optimize operations. BIM-enabled retrofits have shown energy and daylighting improvements in similar contexts [16]. The low-**cost**, modular design makes deployment feasible even without full-time technical staff, and well-structured data can be shared publicly to engage communities in sustainability initiatives.
- **Non-building assets:** The semantic architecture of the proposed framework can be extended beyond buildings to encompass broader infrastructure assets such as bridges, pipelines, and other civil structures. This generalization requires integrating domain-specific ontologies. For instance, the Building Topology Ontology (BOT) could be expanded or substituted with infrastructure-oriented models capable of representing components like decks, piers, abutments, or flow systems and network elements such as pipes and valves. The broader architecture, covering data acquisition, IoT integration, and real-time synchronization, remains applicable. Extending the ontology layer ensures that asset-specific entities and relationships are rigorously defined, enabling consistent, interoperable data exchange across diverse infrastructure domains.
- **Cloud–edge computing framework:** Integrating the proposed CDE into a cloud–edge computing framework can markedly enhance real-time synchronization and **system** responsiveness. In this hybrid configuration, edge devices situated near IoT sensors handle preprocessing, filtering, and semantic structuring of data, while the cloud hosts centralized repositories and executes computationally intensive analytics. Edge gateways may operate lightweight triple stores that convert raw sensor streams into standardized RDF triples before asynchronously transmitting updates to the cloud knowledge graph. This distributed setup combines the low-latency advantages of local processing with the scalability and consistency of cloud infrastructure. It also maintains operational continuity under unstable network conditions, as edge nodes cache data during disconnections and synchronize once connectivity is restored. Overall, the cloud–edge integration improves throughput, reliability, and decision-making efficiency across all project stakeholders.
- **Blockchain-based system:** Integrating a blockchain-based provenance layer can enhance the semantic Common Data Environment (CDE) by providing a distributed, tamper-resistant ledger for recording all data transactions. While the semantic model ensures interoperability and structured data linkage, the blockchain layer secures every modification with immutable timestamps and verifiable origins. This is particularly valuable in decentralized or multi-stakeholder environments, where numerous contributors upload sensor data, BIM models, or project documents. By hashing each record and storing it on the blockchain, the system establishes a transparent and auditable history of data integrity. Smart contracts can further automate governance processes, such as on-chain approvals for design modifications, ensuring rule compliance. Although blockchain integration introduces additional costs and complexity, its selective application to critical datasets significantly strengthens trust, accountability, and data reliability across the digital twin ecosystem.

7. Conclusion

This study proposed a semantic-enabled Common Data Environment (CDE) architecture specifically developed to support real-time Digital Twin (DT) deployment in small-scale construction projects. By integrating modular system design with an ontology-driven semantic layer, the framework achieves seamless interoperability across heterogeneous datasets spanning design, construction, and operational stages. The proposed system unifies static Building Information Modeling (BIM) data with dynamic Internet of Things (IoT) sensor streams, forming a continuous feedback loop that enables real-time monitoring and data-informed decision-making. The Semantic Mapping Process and Data Pipelines are clearly defined within the framework to ensure structured data flow, automated transformation, and consistent semantic alignment among different information sources. The architecture's loosely coupled design, standardized information containers, and use of open data standards ensure scalability, maintainability, and cost efficiency, making it highly suitable for resource-constrained environments. The findings from a case study demonstrate that small-scale projects can achieve advanced DT functionalities through modularity and semantic interoperability without relying on complex or expensive infrastructures.

Future research should focus on three major directions. First, automating the semantic mapping and data integration mechanisms will minimize manual intervention and expedite deployment. Second, enhancing cybersecurity through encryption, role-based access control, and blockchain-based data validation will strengthen data integrity and stakeholder confidence. Third, extending the application of the proposed framework to other domains, such as civil infrastructure, facility management, or heritage conservation, will further validate its flexibility and generalizability. By pursuing these directions, the semantic-enabled CDE provides a robust foundation for advancing Digital Twin adoption and promoting a more connected, intelligent, and sustainable built environment.

8. Declarations

8.1. Author Contributions

Conceptualization, N.N.M.; methodology, N.N.M.; software, N.N.M. and T.N.T.; validation, N.M. and T.N.T.; formal analysis, N.M. and T.N.T.; investigation, N.M. and T.N.T.; resources, N.M. and T.N.T.; data curation, N.M. and T.N.T.; writing—original draft preparation, N.N.M.; writing—review and editing, N.N.M. and T.N.T.; visualization, N.N.M.; supervision, N.N.M.; project administration, N.N.M.; funding acquisition, N.N.M. and T.N.T. All authors have read and agreed to the published version of the manuscript.

8.2. Data Availability Statement

The data presented in this study are available in the article.

8.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

8.4. Conflicts of Interest

The authors declare no conflict of interest.

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