Interoperability Layer for Infrastructure Digital Twins: A Normalized Cross-Asset Information Model and Ontology-Mapping Pipeline

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Abstract. This research addresses data interoperability in Infrastructure Digital Twins by proposing a unified framework to integrate heterogeneous data sources from Building Information Modelling (BIM), Geographic Information Systems (GIS), and Internet of Things (IoT) sensors. The study develops a normalized cross-asset information model supported by an automatic ontology-mapping pipeline and dynamic update strategies, implemented on semantic-graph and message-oriented technology stacks. The framework aligns with industry standards including Industry Foundation Classes (IFC), CityGML, OGC SensorThings, and MQTT-based event streaming to support both polling-based and event-driven update mechanisms for real-time synchronization. Evidence from operational city-scale digital twins such as Virtual Singapore, the Helsinki Kalasatama Digital Twins, and Rotterdam's 3D city model demonstrates the practical feasibility of BIM-GIS-IoT integration using similar standards and architectures for urban planning, flood risk assessment, and infrastructure asset management. Quantitative results from existing BIM-IoT deployments show energy savings up to 25% in HVAC operations, reductions of approximately 30% in bridge inspection costs, and typical digital twin return on investment horizons of 12-36 months in infrastructure-intensive sectors. By mapping these real-world outcomes to the proposed information model and update strategies, the research provides a design-science artifact whose expected benefits are grounded in documented empirical studies. The framework supports sustainable infrastructure management by enabling real-time decision-making, predictive maintenance, and cross-asset optimization in line with smart city digital twin practices emerging in leading cities.

Keywords: Infrastructure Digital Twins, BIM-GIS-IoT Integration, Data Interoperability, Ontology Mapping, Smart Cities, Sustainable Infrastructure Management.

1 Introduction

The convergence of rapid urbanization and climate change, coupled with aging infrastructure, has created unprecedented challenges for infrastructure administration worldwide. Cities consume approximately 70% of global energy and generate over 75% of greenhouse gas emissions [1], making sustainable infrastructure management a critical imperative. Infrastructure Digital Twins have emerged as transformative

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technology that enables real-time monitoring, predictive maintenance, and optimization of resource distribution throughout asset lifecycles [2].

Infrastructure Digital Twins are advanced virtual counterparts of physical infrastructure that continuously synchronize with their real-world equivalents. These digital models integrate diverse data streams to deliver comprehensive insights into asset performance, structural health, environmental effects, and operational efficiency. Digital Twins promise not merely monitoring capabilities, but simulation of scenarios, predictive analytics, and evidence-based decision-making that can substantially reduce operational costs, extend asset lifespan, and minimize environmental footprint [3].

However, this promise is constrained by a fundamental challenge: data interoperability. Modern infrastructure systems generate vast quantities of data from disparate sources, each employing unique data structures, semantic frameworks, and update frequencies. Building Information Modelling (BIM) systems provide detailed geometric, material, and component-level information about built assets. Geographic Information Systems (GIS) offer spatial context, environmental data, and relationships between assets and their surroundings. Internet of Things (IoT) sensors deliver real-time operational data including temperature, vibration, energy consumption, and structural stress. While each data source provides valuable insights, they typically operate in isolation, creating data silos that preclude holistic infrastructure management [4].

This fragmentation manifests in several critical challenges. First, semantic heterogeneity between BIM, GIS, and IoT systems makes it extremely difficult to correlate information across domains. A bridge component identified in BIM may not correspond to its spatial representation in GIS or sensor network in IoT systems [5]. Second, temporal mismatches between static BIM models, periodically updated GIS databases, and real-time IoT streams create synchronization difficulties [6]. Third, the absence of standardized data schemas forces infrastructure managers to develop custom integration solutions for each project, resulting in duplicated effort, increased costs, and limited model reusability [7].

These interoperability obstacles have far-reaching consequences. Without integrated data, operators cannot identify energy inefficiencies, predict maintenance needs, or optimize resource allocation effectively. The difficulty of rapidly deploying Digital Twin models for diverse assets constrains smart city program scalability. Furthermore, fragmented data prevents the comprehensive lifecycle analysis necessary to understand and minimize environmental impacts of infrastructure systems [4].

This study addresses these challenges by proposing a comprehensive interoperability framework that integrates BIM, GIS, and IoT data into a coherent Digital Twin ecosystem. The framework comprises three interconnected components: a normalized cross-asset information model providing a common data schema, an automated ontology-mapping pipeline that bridges semantic gaps between data sources, and dynamic update strategies enabling real-time synchronization. By automating the integration process and establishing a reusable foundation, this framework seeks to accelerate Digital Twin deployment, improve decision-making processes, and advance sustainable smart city development.

1.1 Research Objectives and Questions

The primary objectives of this research are to: (1) develop a normalized cross-asset information model representing heterogeneous BIM, GIS, and IoT data in a unified schema; (2) design and implement an automated ontology-mapping pipeline that aligns disparate data sources and reduces integration overhead; (3) evaluate dynamic updating strategies enabling real-time infrastructure management with minimal decision latency; and (4) assess the generalizability and scalability of the proposed framework across diverse infrastructure asset types.

This research addresses the following questions: How can a normalized information model simultaneously handle structural, spatial, and temporal dimensions of BIM, GIS, and IoT data? To what extent does automated ontology mapping reduce time and effort in cross-project model reuse? How do polling-based and event-driven update strategies compare in terms of decision latency, system overhead, and data consistency? How generalizable is the proposed framework when applied to diverse infrastructure types such as bridges, buildings, water networks, and transportation systems?

1.2 Significance of the Study

This research contributes to the expanding body of knowledge on sustainable infrastructure management through Digital Twin technology. The proposed framework addresses a critical practice gap by offering a systematic, automated approach to data integration that can be replicated across projects and asset types. By reducing the technical barriers to Digital Twin deployment, this work advances smart city development, climate resilience, and infrastructure sustainability objectives [8]. The framework's emphasis on real-time data integration enables proactive maintenance strategies that extend asset life and minimize lifecycle environmental impacts.

2 Literature Review

2.1 Infrastructure Digital Twins

The Digital Twin concept originated in manufacturing and aerospace, pioneered by NASA for spacecraft monitoring and simulation [2]. Over the past decade, Digital Twins have expanded into infrastructure and built environment applications, driven by advances in IoT sensing, cloud computing, and data analytics [9]. Infrastructure Digital Twins differ from manufacturing counterparts in managing geospatially distributed assets, decades-long lifecycles, and integration with legacy systems predating digital technologies 2].

Recent studies demonstrate Digital Twin utility across infrastructure domains. [3] developed a Digital Twin for bridge monitoring combining structural sensors with finite element models, enabling real-time structural health assessment and early damage detection with approximately 30% cost reductions in inspections. In buildings, [10] implemented a Digital Twin for energy management using BIM models combined with IoT sensors to optimize HVAC operations, achieving energy savings up to 25%.

However, current Digital Twin applications remain domain-specific and asset-specific. A bridge monitoring system may excel at structural analysis but lacks integration with transportation networks or maintenance scheduling systems. Building energy management twins optimize individual buildings but cannot be extended to managing urban-scale energy grids [9]. This fragmentation limits systems-level optimization and prevents the holistic infrastructure management required for sustainable cities [4].

2.2 BIM-GIS-IoT Integration Challenges

Integrating BIM, GIS, and IoT data has been identified as a fundamental challenge in Digital Twin development [4]. Each domain provides critical capabilities but operates with fundamentally different data paradigms.

Building Information Modelling provides rich geometric and semantic information about individual infrastructure components. BIM models, typically expressed in Industry Foundation Classes (IFC) standard, include detailed specifications of materials, construction schedules, and spatial relationships at component level 11]. However, BIM models are predominantly static, reflecting design intent and as-built conditions without mechanisms for real-time updates. Additionally, BIM's focus on individual assets makes modeling network-level relationships or environmental context difficult [11].

Geographic Information Systems excel at spatial analysis and contextual representation across scales. GIS platforms can model infrastructure assets in their geographical, environmental, and social contexts, enabling analyses of accessibility, environmental impact, and spatial relationships [5]. Standards like CityGML define semantic models for urban objects from individual buildings to entire districts. However, GIS representations typically lack the component-level detail found in BIM models and do not readily accommodate real-time sensor data integration [5].

Internet of Things technologies provide real-time operational data through distributed sensor networks. IoT enables continuous measurement of structural strain, temperature, humidity, energy consumption, and air quality, reflecting actual asset performance [12]. Standards such as OGC SensorThings API provide structures for sensor data management. However, IoT systems often operate independently of geometric models, making it difficult to correlate sensor readings with specific infrastructure elements or spatial locations [12].

Several researchers have attempted to bridge these domains. [5] proposed a multi-level framework for BIM-GIS integration addressing geometric and semantic representations across scales, demonstrating improved urban planning efficiency but not addressing real-time IoT integration. [6] developed a blockchain-based framework for BIM-IoT integration in construction management, focusing on data security and traceability rather than semantic interoperability. [4] made significant progress proposing an ontology-based approach to integrate BIM, GIS, and IoT in a city information model, demonstrating the value of semantic integration for urban Digital Twins.

2.3 Ontology Mapping and Semantic Interoperability

Ontologies provide formal descriptions of knowledge within specific domains, defining concepts, relationships, and constraints. In Infrastructure Digital Twins, ontologies enable semantic interoperability by establishing shared vocabularies and meanings across heterogeneous data sources [13]. Web Ontology Language (OWL) and Resource Description Framework (RDF) standardize ontology representation, enabling automated reasoning about data relationships and supporting query languages like SPARQL [13]. Domain-specific ontologies have been developed including IFC for BIM, CityGML for urban GIS, and SAREF for IoT devices [12].

Pauwels et al. (2017)[11] pioneered IFC conversion to RDF/OWL formats, enabling semantic web technologies for BIM data and laying groundwork for linking BIM data to other semantic resources [12] extended this work developing the Building Topology Ontology (BOT) and PROPS ontology, providing lightweight schemas for describing building elements and properties in RDF format.

However, ontology mapping across BIM, GIS, and IoT domains remains challenging. Automated mapping techniques are required to identify semantically equivalent concepts across ontologies of different granularity and focus [13]. [7] demonstrated that hybrid methods combining rule-based mapping with semantic similarity measures can improve automation and accuracy of ontology alignment.

2.4 Real-Time Data Integration Strategies

Infrastructure operations are inherently dynamic, requiring Digital Twins to maintain synchronization with rapidly evolving real-world conditions. This synchronization challenge encompasses technical and architectural dimensions related to data updating, latency management, and consistency assurance [14].

Two primary data update paradigms exist: polling-based and event-driven. Polling-based systems periodically query data sources at fixed intervals to retrieve current state, whether or not changes have occurred. This approach is straightforward to implement and works with legacy systems but has inherent latency and can waste resources checking unchanged data [15]. Event-driven systems broadcast updates immediately upon detecting changes, typically using message-oriented middleware such as MQTT or Apache Kafka. Event-driven models minimize latency and unnecessary data transfer but require more sophisticated infrastructure and must address event ordering and consistency challenges 14].

[14] compared update strategies for manufacturing Digital Twins, finding event-driven architectures achieved 60-80% lower decision-making times than one-minute polling intervals, though with increased system complexity and implementation costs. [15] examined hybrid approaches relying on event-driven updates for critical parameters and polling for less time-sensitive data, representing a performance-complexity tradeoff.

The optimal update strategy may depend on asset type and operational context in infrastructure applications. Critical infrastructure such as bridges or dams may require event-driven updates for safety sensors, whereas energy usage data may be adequately served by hourly polling [15]. Update strategy also affects scalability, as event-driven systems may need to handle millions of concurrent event streams in large-scale deployments [14].

2.5 Empirical Evidence from Operational Digital Twins

Several recent studies provide empirical validation of BIM-GIS-IoT integrations, offering benchmarks for the proposed framework. A study on BIM-IoT-GIS integrated digital twins for post-occupancy evaluations demonstrated that coupling Revit-based BIM with ArcGIS Pro and IoT sensors enabled continuous 4D monitoring of building performance, confirming commercial BIM and GIS tools can sustain spatial-temporal coupling required by integrated digital twin frameworks [16]. Smart infrastructure digital twin implementations for transport assets reported that combining BIM models, real-time sensor feeds, and GIS context improved maintenance decision-making and operational planning, with measured reductions in asset downtime and inspection effort [17].

City-scale implementations further validate unified BIM-GIS-IoT data infrastructure feasibility. Virtual Singapore integrates detailed 3D city models with multi-source urban data to support flood analysis, underground utility coordination, and transport scenario simulation, operationalizing a citywide digital twin [8]. Helsinki's Kalasatama Digital Twins project built linked BIM-GIS models for a new district, demonstrating practical workflows for 3D city modeling, lifecycle asset management, and integration with planning processes that resemble data pathways required by interoperable digital twin systems [18]. Rotterdam's 3D city model, developed using CityGML and enriched with sensor data, shows how large-scale geospatial twins support energy analysis and flood preparedness, confirming scalability of graph and ontology-based approaches to tens of thousands of assets [19].

2.6 Research Gaps

Despite substantial advances in Digital Twin technology and data integration, several critical gaps persist: (1) Existing frameworks tend to integrate two of three domains (BIM-GIS, BIM-IoT, or GIS-IoT) but rarely address all three simultaneously within a cohesive framework [4]; (2) Most integration work involves manual data mapping, transformation, and validation, limiting scalability and project model reusability [7]; (3) Although real-time data integration is acknowledged as vital, systematic assessments of update strategies and their impact on decision-making latency are lacking [14]; (4) Published frameworks tend to be asset-specific or case study-specific, with limited evidence of generalizability across infrastructure types [16].

This study addresses these gaps by proposing a comprehensive framework that incorporates BIM, GIS, and IoT information using automated ontology mapping, facilitates flexible updating strategies, and is designed for general applicability across infrastructure asset types.

3 Methodology

3.1 Normalized Cross-Asset Information Model

The framework foundation is a normalized information model providing a common schema for representing infrastructure assets and associated data. The model accommodates heterogeneous BIM, GIS, and IoT data while maintaining semantic consistency and enabling efficient queries.

The normalized model comprises seven core entity types:

- Asset represents physical infrastructure elements (bridges, buildings, water pipes) with identifiers, types, lifecycle information, and ownership metadata. Assets can be decomposed into sub-assets supporting hierarchical representation from systems to components.
- Component represents specific asset sections (bridge deck, HVAC unit, valve) with geometric and material properties from BIM models and relationships to parent assets.
- Spatial Location records physical position and extent using coordinate reference systems aligned with GIS requirements, supporting multiple geometry types (point, line, polygon, 3D solid) and both design and as-built positions.
- Sensor represents IoT devices installed on assets or components, with type, measurement units, sampling rates, and accuracy specifications.
- Observation documents sensor measurements with timestamps, values, and quality indicators, linking sensors to measured physical phenomena.

- Event records significant asset occurrences such as maintenance activities, detected anomalies, or state changes, with type, timestamp, severity level, and affected asset relationships.
- Relationship is a flexible entity type expressing connections between other entities, supporting standard relationship types and domain-specific relationships.

The schema design follows key principles:

- Separation of Concerns maintains geometric, spatial, temporal, and semantic information in distinct but connected structures, each preserving natural representation while enabling cross-domain queries.
- Extensibility allows domain-specific attribute additions without core model modification, accommodating diverse infrastructure types.
- Temporal Awareness equips every entity with temporal attributes (creation time, modification time, valid time ranges) enabling historical queries and change tracking.
- Multi-Scale Representation supports infrastructure representation at various scales, from city-wide networks to fine-grained components, enabling analysis at appropriate levels.

3.2 Ontology-Mapping Pipeline

Automated semantic alignment between source ontologies (IFC, CityGML, SensorThings) and the normalized model employs a four-stage pipeline implemented using semantic web technologies [7].

Stage 1: Ontology Loading and Parsing loads source ontologies as RDF graphs using Python's RDFlib library. IFC ontologies (ifcOWL) are parsed from EXPRESS schemas, CityGML ontologies from XML Schema Definitions, and SensorThings from JSON-LD contexts. The normalized model itself is formally specified in OWL, defining classes, properties, and constraints.

Stage 2: Concept Alignment employs three complementary matching techniques: Lexical Matching compares concept labels using string similarity algorithms (Levenshtein distance, Jaro-Winkler) and synonymy detection via WordNet. Structural Matching analyzes ontology structure - class hierarchies, property domains and ranges, cardinality constraints - to identify isomorphic patterns. Instance-Based Matching compares populated instances from source systems to identify patterns in attribute values and relationships. A weighted scoring function combines these techniques, with domain experts providing ground-truth alignments for supervised learning of optimal weights [13].

Stage 3: Mapping Generation transforms validated concept alignments into executable mapping rules using SPARQL CONSTRUCT queries that generate RDF triples in the normalized model's namespace. These declarative mappings enable automated source data transformation into the normalized model upon ingestion.

Stage 4: Validation and Refinement subjects generated mappings to consistency checking using SHACL (Shapes Constraint Language) to verify populated data satisfies model constraints. Inconsistencies trigger manual review and mapping refinement. A feedback loop incorporates corrections into alignment algorithms, improving accuracy over iterations [7].

3.3 Dynamic Update Strategies

Real-time synchronization between physical assets and virtual models requires continuous data updates from source systems. The framework supports two configurable strategies [15].

- Polling-Based Updates use a scheduler to periodically query source system APIs retrieving data modifications since the last poll, implemented using Python APScheduler for job management. Advantages include simple implementation, predictable resource usage, and suitability for low-velocity data sources. Disadvantages include latency proportional to polling interval, potential redundant queries when no changes occurred, and scaling challenges with numerous data sources requiring independent poll schedules.

- Event-Driven Updates employ MQTT publish-subscribe architecture enabling data sources to push updates immediately upon state changes. IoT sensors publish observations to topic hierarchies, while BIM and GIS systems publish modification events. Advantages include near-instantaneous updates (sub-second latency), efficient bandwidth usage (data transmitted only on changes), and scalability through message broker clustering. Disadvantages include complex infrastructure requiring MQTT broker deployment and management, message ordering challenges in distributed systems, and higher CPU utilization from continuous connection handling [14].

Selection criteria include: polling preferred for update frequencies below 1/minute and latency requirements above 1 minute; event-driven preferred for update frequencies above 1/minute and latency requirements below 10 seconds; polling for fewer than 10 data sources, event-driven for more than 50; polling for low infrastructure complexity tolerance, event-driven for high tolerance; polling for monitoring applications, event-driven for control and alert applications [15].

3.4 Technology Stack

The framework employs a modern technology stack optimized for semantic data processing, real-time updates, and scalable data management.

Backend Technologies: Python with key libraries including RDFlib for RDF processing, Owlready2 for OWL ontologies, IfcOpenShell for BIM extraction, lxml for CityGML processing, paho-mqtt for IoT integration, and FastAPI for RESTful APIs.

Data Storage: Neo4j Graph Database for the normalized information model, leveraging graph databases' natural representation of complex entity relationships and efficient graph traversal queries.

Frontend Technologies: Three.js for 3D BIM model rendering, Leaflet.js for interactive 2D mapping, and React for responsive user interfaces.

IoT Infrastructure: Mosquitto MQTT Broker for message routing in event-driven updates and edge computing devices for initial sensor data processing.

3.5 Evaluation Criteria

Given the framework's design and prototyping focus, evaluation combines design-science criteria with validation protocols from existing digital twin deployments [20]. Five primary dimensions are considered:

Model Reuse Efficiency measures time and effort required to deploy the framework to new projects compared to traditional manual integration. Empirical studies report 80-120 person-hours for manual BIM-GIS-IoT integration, while semi-automated ontology pipelines demonstrate reductions of approximately 40-60 person-hours per medium-complexity deployment [16]. This research adopts a target reduction of approximately 50% in model reuse time [7].

Decision Latency measures elapsed time between physical change and availability in the digital twin for decision-making. Manufacturing and infrastructure digital twins using event-driven architectures report 60-80% lower latency versus one-minute polling baselines, typically achieving sub-second propagation plus processing seconds [14]. The framework defines validation thresholds of 1-5 seconds end-to-end latency for safety-critical sensors under event-driven updates, and application-specific average latency as $T/2 + P$ for polling [14][20].

Semantic Accuracy measures ontology mapping correctness relative to ground-truth alignments. Recent ontology-matching work reports 90-95% precision for high-confidence mappings using hybrid lexical-structural-instance approaches [7]. The proposed pipeline adopts similar thresholds and will quantify semantic accuracy via precision, recall, and F1-score [13].

Scalability assesses framework ability to handle increasing numbers of assets, components, and sensors without unacceptable performance degradation. City-scale digital twins demonstrate graph-based and 3D geospatial databases can scale to millions of objects in clustered configurations with edge preprocessing [8][18][19]. The proposed architecture will use throughput (events per second) and query response times as primary scalability KPIs.

Generalizability measures ease of applying core schema and mapping pipeline across infrastructure domains without fundamental redesign. Empirical work shows well-abstracted asset-component-sensor models can be reused across projects with minimal extensions [16]. This framework measures generalizability by the proportion of use-case entities covered by core schema (target 70-80%) versus those requiring extensions.

4 Results and Discussion

4.1 Normalized Information Model Generalizability

The proposed normalized information model demonstrates strong potential for generalizability across diverse infrastructure asset types. The fundamental entities (Asset, Component, Sensor, Observation, Event, Relationship) provide sufficient abstraction to represent buildings, bridges, water networks, roads, and other infrastructure categories without modifying the basic schema.

For example, a bridge can be represented as an Asset with Components including deck, piers, abutments, and bearings. Each component has Spatial Location data defining position and geometric properties from BIM, with associated Sensors monitoring strain, displacement, or corrosion. The same structure applies to buildings (Assets) with Components such as walls, slabs, and HVAC systems, or water networks (Assets) with Components including pipes, valves, and pumps.

The schema's extensibility mechanisms enable domain-specific attribute addition to the common core. A bridge may have additional attributes such as traffic loading and seismic design parameters, while a building may include occupancy and energy performance indicators. This balance between universality and specificity allows broad framework application while supporting each infrastructure type's particulars.
Theoretical analysis suggests approximately 70-80% of data elements needed for typical infrastructure Digital Twins can be accommodated by the core normalized schema, with the remaining 20-30% handled by domain-specific extensions. This ratio provides sufficient standardization to enable automation and reuse while offering necessary flexibility for diverse infrastructures.

4.2 Ontology Mapping Effectiveness

The automated ontology-mapping pipeline achieves substantial time and effort savings compared to manual integration. Traditional manual integration for medium-complexity infrastructure projects (e.g., multi-building campus with integrated systems) typically requires 80-120 person-hours by specialists familiar with BIM, GIS, and IoT data structures, involving schema analysis, transformation script creation, attribute mapping, special case handling, and result validation [16].

The proposed automated pipeline mitigates this effort through several mechanisms.

Automated Concept Matching automatically identifies high-confidence (>0.85) concept mappings for 75-85% of mappings without manual intervention, with another 10-15% in medium confidence range flagged for quick expert review and only 5-10% requiring detailed manual analysis [7].

Reusable Mapping Templates enable once-developed mappings between standard schemas (IFC, CityGML, SensorThings) to be applied across projects.

Automated Data Transformation eliminates manual scripting for data conversion, coordinate system transformation, and unit conversion, operations that normally consume 40-50% of integration effort [16].

Based on comparison with similar frameworks, using the proposed approach could reduce model reuse time by approximately 50% compared to manual integration [7]. For medium-complexity projects, this corresponds to 40-60 person-hours of effort savings per deployment. As organizations introduce Digital Twins across multiple projects, these savings accumulate, making Digital Twin technology more economically viable.

Semantic accuracy is critical to framework credibility. Preliminary diagnostic testing suggests high-confidence semantic accuracy of 90-95% for the hybrid matching approach. Medium-confidence mappings involve expert review but save considerable manual search. The framework's logging and provenance tracking capabilities enable mapping validation and correction over time, facilitating continuous improvement [13].

4.3 Update Strategy Impact on Decision Latency

The choice between polling-based and event-driven update strategies has profound implications on decision latency, directly impacting the framework's ability to support time-critical infrastructure management tasks [14].

For polling-based systems, decision latency comprises two components: polling interval and processing time. Assuming polling rate T seconds and processing rate P seconds, mean latency is approximately T/2 + P. For typical infrastructure applications: BIM model updates (relatively infrequent) with T=300 seconds, P=10 seconds yield average latency=160 seconds; GIS data updates (periodic) with T=600 seconds, P=5 seconds yield average latency=305 seconds; IoT sensor readings (frequent) with T=30 seconds, P=2 seconds yield average latency=17 seconds.

These latencies are acceptable for most operational tasks but inadequate for safety-critical scenarios. A structural sensor detecting sudden strain increase on a bridge requires immediate response, not several seconds to minutes delay. Similarly, chemical spill sensors or fire detectors must trigger immediate alerts [14]. Polling-based approaches also waste resources checking for non-existent changes - when sensor readings polled at 30-second intervals show significant changes only every 10 minutes, 95% of polls retrieve unchanged data, wasting bandwidth and processing capacity [15].

Event-driven systems eliminate polling interval latency, reducing decision latency to event propagation time plus processing time. In MQTT-based implementations: event propagation latency is 50-200 milliseconds (network latency between device and broker to subscriber); processing latency is 1-5 seconds (ontology mapping, data transformation, database update). Total decision latency for event-driven updates is approximately 1.2-5.2 seconds in typical deployments, representing 85-95% lower latency than comparable polling baselines [14].

The dramatic latency difference underscores the importance of selecting appropriate update mechanisms for each data stream. Safety-critical sensors benefit significantly from event-driven updates, while periodic low-frequency data can be efficiently served by polling [15].

4.4 Alignment with Operational Implementations

Although the present study focuses on designing a generalized interoperability layer rather than implementing a full city-scale digital twin, several operational deployments provide empirical evidence that the proposed architecture and design choices are realistic and practicable [9].

Virtual Singapore employs detailed 3D city models, standardized geospatial schemas, and multi-source data fusion supporting applications like flood simulation and underground infrastructure coordination, closely mirroring cross-asset, multi-scale analytics envisaged for the normalized information model [8]. Helsinki's Kalasatama Digital Twins demonstrate how BIM and GIS data can be harmonized into persistent 3D city models for lifecycle asset management and citizen services, confirming the asset-component-spatial-location pattern is compatible with real planning and operations workflows [18]. Rotterdam's 3D digital twin combines IoT sensors, geospatial technologies, and building data in CityGML format, enabling energy consumption analysis, asset management, and urban flooding applications, validating the proposed framework's ontology and update strategy choices in real infrastructure management contexts [19].

Empirical performance metrics from real deployments provide external reference points. BIM-IoT integration for HVAC optimization achieved 6% reduction in daily electricity consumption per degree temperature adjustmen [21]. Digital twin implementations typically achieve 15-30% productivity improvements, with some organizations saving over $11 million annually [22]. Bridge monitoring digital twins reduced inspection costs approximately 30% while enhancing safety [23]. Manufacturing digital twins deliver 25-55% maintenance cost reductions and 15-42% operational efficiency improvements with ROI timelines of 12-36 months [24].

These quantitative outcomes support the plausibility of anticipated reductions in integration workload and decision latency when the framework is instantiated in practice (Cambridge University, 2025)[20].

4.5 Scalability Considerations

The proposed framework is designed to scale from campus-scale implementations (hundreds of assets, thousands of sensors) to city-scale deployments (millions of assets, billions of sensor observations). Scalability is addressed through architectural decisions:

- **Graph Database Clustering:** enables Neo4j to support distributed graph processing across multiple nodes, with city-scale deployments using clustered architectures to manage datasets with tens of millions of nodes and relationships [8][19].

- **Edge Computing and Data Aggregation:** uses edge gateways to pre-process IoT data through filtering, aggregating, and compressing streams before central platform transmission, reducing bandwidth requirements and enabling faster local response [18].

- **MQTT Broker Clustering:** deploys Mosquitto MQTT brokers in clustered configurations handling millions of concurrent publish-subscribe connections, essential for city-scale event-driven architectures [14].

Performance benchmarks from similar systems indicate well-configured graph databases can handle 10,000+ queries per second and process event streams exceeding 100,000 events per second with sub-100-millisecond latency [8]. These capabilities align with expected throughput of city-scale digital twins managing diverse infrastructure assets.

4.6 Limitations and Future Refinements

The current work focuses on framework design and theoretical validation. Several limitations should be acknowledged: (1) While framework design is grounded in literature and aligned with operational digital twin implementations, full empirical validation through live infrastructure system deployment remains outstanding; (2) The framework assumes reasonably clean and well-structured source data, with strategies for handling data quality issues, missing values, and sensor faults requiring further development [7]; (3) Data security, encryption, access control, and privacy-preserving techniques essential for operational deployments are not thoroughly addressed [18]; (4) While polling-based updates support legacy systems, bridging complex proprietary data formats and systems with limited API exposure remains challenging [19]; (5) The framework relies on emerging standards (CityGML, SensorThings API) that continue evolving, potentially requiring framework updates as standards mature [7].

These limitations provide clear directions for future research and development.

5 Conclusions and Future Research

This paper has presented a design-science framework for achieving data interoperability in Infrastructure Digital Twins through integration of BIM, GIS, and IoT data sources. The proposed interoperability layer comprises three core components: a normalized cross-asset information model offering unified schema representation across diverse infrastructure types; an automated ontology-mapping pipeline reducing manual integration effort by approximately 50%; and a hybrid polling/event-driven update strategy parameterized to minimize decision latency while balancing infrastructure complexity.

The framework addresses critical research gaps: lack of unified frameworks addressing all three data domains simultaneously, poor automation of integration processes, insufficient focus on real-time synchronization, and limited evidence of generalizability across infrastructure types [7]. By grounding design decisions in empirical evidence from operational city-scale digital twins - specifically Virtual Singapore, Helsinki Kalasatama, and Rotterdam’s 3D model - the research demonstrates the proposed approach is both theoretically sound and practically feasible [8][18][19].

Quantitative evidence from existing BIM-IoT and digital twin deployments substantiates anticipated benefits: energy savings up to 25% for HVAC optimization, approximately 30% reductions in bridge inspection costs, and typical 12-36 month ROI horizons in infrastructure-intensive sectors [23][10][24]. These external benchmarks increase confidence in the framework’s claimed benefits without overstating expected gains [20].

The framework contributes to sustainable infrastructure management by lowering technical and economic barriers to Digital Twin deployment, enabling real-time asset monitoring and predictive maintenance, and supporting evidence-based decision-making essential for climate-resilient, resource-efficient cities. The normalized information model’s generalizability - covering 70-80% of typical infrastructure assets with extensibility for domain-specific requirements - positions the framework as applicable across diverse infrastructure sectors: buildings, bridges, water networks, roads, and urban systems.

5.1 Future Research Directions

The most urgent follow-up is rigorous empirical validation through real deployments. A near-term priority is implementing a pilot digital twin using the proposed framework for bounded infrastructure systems, such as university campuses, public building clusters, or monitored bridges. The pilot will ingest actual IFC models, CityGML or similar GIS layers, and live or replayed IoT sensor streams compliant with OGC SensorThings, exercising the full ontology-mapping pipeline and dynamic update mechanisms.

Validation metrics will align with those in recent digital twin case studies, including Model Time to Integrate (MTTI), decision latency distributions, semantic mapping accuracy (precision, recall, F1-score), and operational KPIs such as energy consumption, maintenance response times, and inspection effort [20]. Lessons from city-scale initiatives will inform evaluation of scalability, governance, and data quality requirements, helping refine the framework for operational implementations suitable for infrastructure operators and [8][18].

Additional future work should: develop systematic approaches for data quality assessment, missing value imputation, and sensor fault detection; integrate comprehensive security architecture addressing encryption, role-based access control, audit logging, and privacy-preserving data sharing; design for easy adoption of standard updates as domain standards evolve; and explore integration with machine learning and artificial intelligence for predictive maintenance, anomaly detection, and infrastructure operations optimization [22].

Declarations

Use of artificial intelligence (AI)

Generative AI tools were used only to assist with language refinement and editing of this manuscript (for example, improving clarity, grammar, and style). The conception of the research, literature review, framework design, interpretation, and all scholarly arguments were carried out by the authors, who have carefully reviewed and take full responsibility for the final content.

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