International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 08 , August - 2026

Ontologically Integrated Digital Twin of the Entire Hospital Ecosystem

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Abstract - The rapid evolution of Healthcare 5.0 demands intelligent hospital ecosystems capable of integrating clinical care, operational management, and physical infrastructure into a unified, continuously adaptive environment. However, contemporary healthcare information systems remain fragmented across Electronic Health Records (EHRs), Internet of Medical Things (IoMT) devices, laboratory systems, imaging platforms, and Building Management Systems (BMS), resulting in severe data siloing, limited semantic interoperability, delayed decision-making, and inadequate real-time situational awareness. Although digital twin technology has emerged as a promising paradigm for creating virtual representations of physical entities, existing healthcare implementations are largely confined to isolated organs, medical devices, or specific clinical workflows, thereby failing to support hospital-wide intelligence and cross-domain reasoning. This paper proposes the Ontologically Integrated Digital Twin (OIDT) framework, a comprehensive and semantically enriched architecture for constructing a scalable, hospital-wide digital twin capable of synchronizing physical, cyber, and organizational processes in real time. The framework is founded on a formal Web Ontology Language (OWL) knowledge model, termed HospitalOnt, which unifies heterogeneous healthcare and infrastructure data by aligning internationally recognized standards including SNOMED CT, LOINC, RxNorm, HL7 FHIR, and the W3C SSN/SOSA sensor ontologies. Through this semantic foundation, OIDT enables machine-understandable relationships among patients, clinicians, medical devices, hospital assets, environmental sensors, workflows, and facility resources. A distributed five-layer architecture is presented, comprising Physical Sensing, Edge Intelligence, Streaming Integration, Semantic Knowledge, and Application Intelligence layers. Real-time data acquisition is achieved through IoMT devices, environmental sensors, and operational systems connected via MQTT and FHIR interfaces. The streaming backbone employs Apache Kafka and Apache Flink for high-throughput ingestion, semantic annotation, event processing, and temporal synchronization. Multi-model persistence is implemented using Neo4j for graph-based knowledge representation, InfluxDB for time-series telemetry, and PostgreSQL for transactional healthcare data, thereby supporting both analytical and operational workloads. To demonstrate intelligent decision support, OIDT integrates multiple AI and simulation components. An LSTM Autoencoder performs predictive maintenance of critical medical equipment, detecting latent degradation patterns before failure. A Prophet-based forecasting model predicts emergency department (ED) patient arrivals and bed occupancy trends, while a Discrete-Event Simulation (DES) engine evaluates alternative resource-allocation strategies under varying operational conditions. The semantic knowledge graph further enables graph-based reasoning and contextual inference, allowing cross-domain queries that combine clinical, operational, and environmental information. The framework was validated on a 200-bed simulated smart hospital testbed incorporating 50 Raspberry Pi edge nodes, synthetic HL7 FHIR event streams, and heterogeneous IoMT telemetry. Experimental results demonstrate substantial operational improvements, including a 28% reduction in average ED waiting time, a 93.0% F1-score for ventilator mechanical failure prediction with a mean lead time of 3.6 hours, an emergency alert propagation latency of 4.1 seconds, representing a 14× improvement over conventional phone-tree workflows, and a 12% reduction in facility energy consumption through context-aware optimization. Semantic interoperability evaluation achieved 96.0% cross-domain query resolution, compared with 24.0% in traditional siloed architectures, while scalability experiments confirmed near-linear performance up to 10,000 concurrent IoT device streams with an average end-to-end latency of 2.1 seconds. In addition to architectural and experimental contributions, the paper formulates mathematical models for graph-based semantic inference, anomaly detection, predictive risk scoring, and energy optimization, and presents a comprehensive security and governance framework based on Zero-Trust architecture, role-based and attribute-based access control, encryption, auditability, differential privacy, and

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 08 , August - 2026

compliance with HIPAA and GDPR. The proposed OIDT framework demonstrates that ontology-driven digital twins can evolve from isolated technological prototypes into a foundational infrastructure for interoperable, resilient, energy-efficient, and AI-enabled smart hospitals, thereby advancing the realization of next-generation Healthcare 5.0 ecosystems.

Index Terms - Digital Twin, Ontology, Knowledge Graphs, Smart Hospitals, Healthcare 5.0, Internet of Medical Things (IoMT), Semantic Interoperability, Predictive Maintenance, Patient Flow Optimization, HL7 FHIR, Deep Learning, Graph Neural Networks, Edge Computing, Real-Time Analytics, Zero-Trust Security.

I. INTRODUCTION

A. Background and Historical Perspective

Healthcare delivery has undergone dramatic structural transformations across successive industrial revolutions. The transition from Industry 4.0—characterized by cyber-physical systems, cloud computing, and pervasive Internet of Things (IoT) connectivity—to Industry 5.0 and Healthcare 5.0 marks a critical paradigm shift. Where Healthcare 4.0 focused heavily on digitizing paper records into Electronic Health Record (EHR) systems and deploying isolated smart devices, Healthcare 5.0 re-centers human-centricity, resilience, and environmental sustainability through deep human-technology collaboration.

In modern hospital environments, this evolution manifests as an explosion of multi-modal, highly heterogeneous data streams. Clinical care now relies on high-frequency vital sign telemetry from intensive care unit (ICU) bedside monitors, continuous wave ECG streams, volumetric medical imaging (DICOM), point-of-care diagnostics, and Real-Time Location Systems (RTLS) tracking staff, patients, and mobile medical assets. Simultaneously, modern medical facilities function as complex smart buildings managed by Building Management Systems (BMS) that regulate heating, ventilation, and air conditioning (HVAC), cleanroom pressurization, lighting, and power distribution.

However, despite the proliferation of digital technologies, contemporary healthcare facilities remain plagued by deep structural fragmentation. Clinical information systems, biomedical engineering asset management platforms, and facility infrastructure software operate in disconnected domain silos. This fragmentation creates critical blind spots: clinical decisions are made without real-time awareness of device maintenance states or ambient environmental parameters, while facility operations are conducted without visibility into patient census shifts or clinical criticality.

B. The Big Data Challenge in Smart Hospitals

The data landscape of a smart hospital is classically defined by the "4 V's" of Big Data, each presenting unique engineering and semantic challenges:

Volume: Modern tertiary hospitals generate terabytes of data daily. A single high-resolution Picture Archiving and Communication System (PACS) study can exceed several gigabytes, while continuously monitored beds generate gigabytes of numeric and waveform data per day per patient.

Velocity: Real-time clinical telemetry demands ultra-low-latency processing. Bedside ECG monitors generate continuous signals sampled at 250 to 500 Hz. RTLS transponders emit location pings at 1 Hz. Ingesting, processing, and acting upon these high-velocity streams before data loses its temporal relevance is a primary systems engineering hurdle.

Variety: Hospital data spans structured relational tables (demographics, billing), semi-structured messaging standards (HL7 v2, HL7 FHIR JSON/XML resources), unstructured clinical notes, binary image series (DICOM), and unstructured sensor telemetry.

Veracity: Data quality challenges are widespread. Physiological sensor streams suffer from motion artifacts, lead disconnects, and calibration drift; manual EHR data entry introduces missing values and delays; and BMS telemetry may exhibit sensor failures. Systems must filter noise and assess data confidence dynamically.

Left unaddressed, these factors result in severe operational inefficiencies and compromised patient safety. Healthcare operations in the United States account for over 30% of total national healthcare expenditure, with billions lost annually to uncoordinated patient transfers, extended Emergency Department (ED) stays, unplanned equipment downtime, and preventable medical errors. A representative operational failure occurs when biomedical engineering has no visibility into early performance degradation in an MRI scanner, while radiology continues to schedule high-priority patients on that asset. When the machine unexpectedly fails, patient care is delayed, staff workflows are disrupted, and emergency repair costs escalate.

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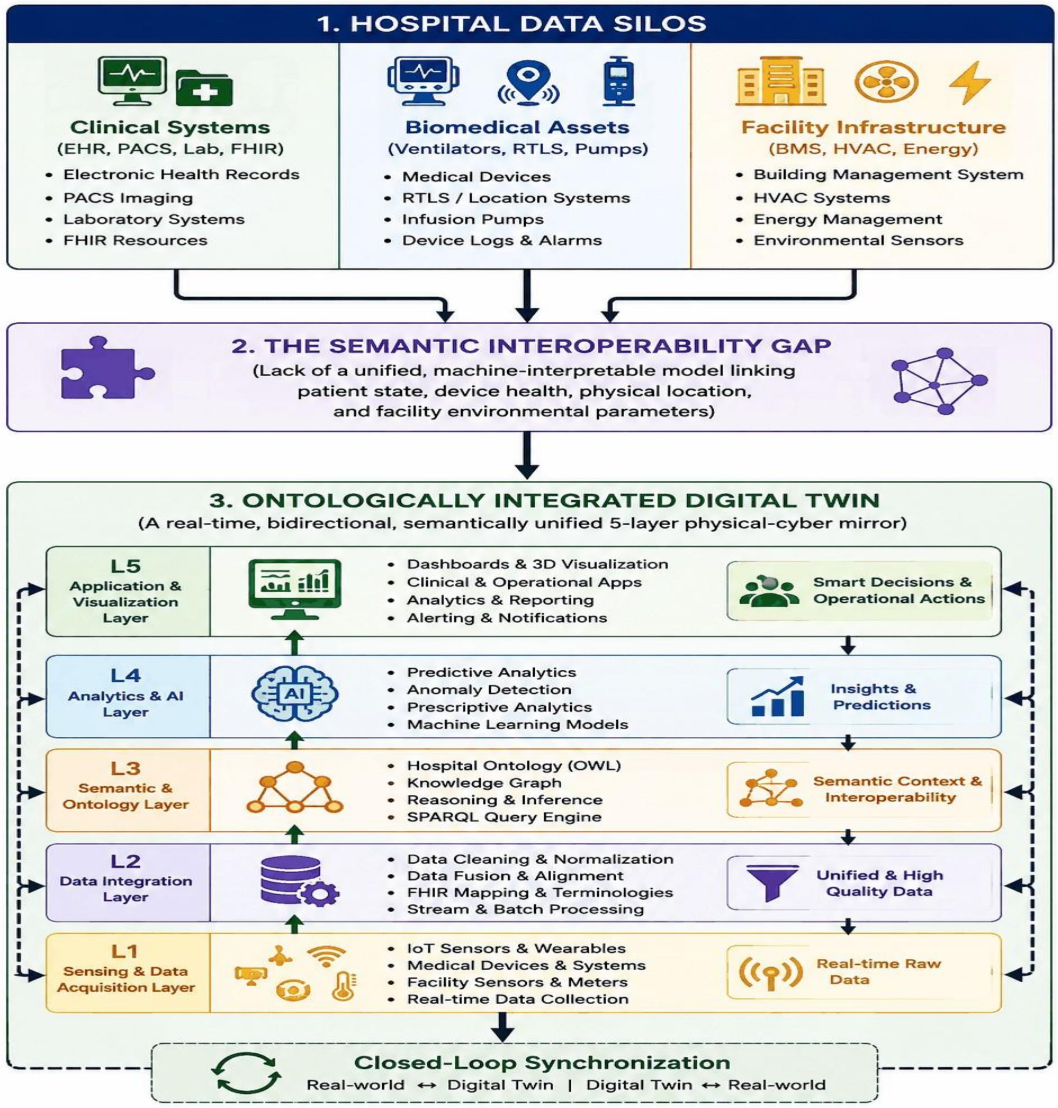

Fig. 1. Hospital Data Silos, Semantic Interoperability Gap, and Ontologically Integrated Digital Twin

C. Digital Twin Concept and Maturity Levels

Digital Twin (DT) technology, originally conceptualized in aerospace and advanced manufacturing, provides a paradigm to resolve this systemic fragmentation. As defined by Kritzinger et al., virtual representations are formally categorized into three distinct maturity levels based on data flow integration:

- Digital Model: A static digital representation of a physical entity with no automated data exchange between the physical and virtual objects. Changes in the physical state do not automatically update the digital model, nor do digital modifications actuate the physical system.
- Digital Shadow: A virtual representation characterized by an automated, one-directional data flow from the physical object to the digital object. Changes in the physical state dynamically update the digital representation in real time, but no automated control flow exists from the digital model back to the physical world.
- Digital Twin: A fully integrated system featuring dynamic, automated, bidirectional data flow between the physical entity and its virtual counterpart. Changes in the physical system immediately propagate to update the virtual model, while analytical inferences, simulations, or optimization algorithms executed in the virtual model feed back automated control actions or actionable alerts to actuate physical workflows or devices.

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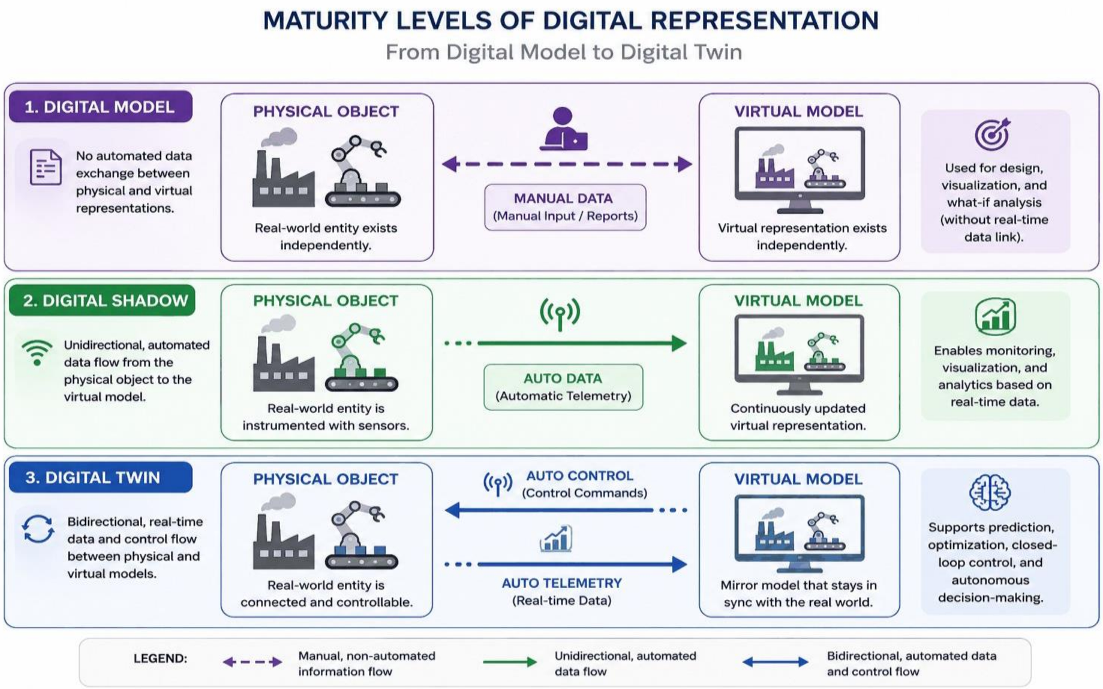

Fig. 2. Maturity Levels of Digital Representation: Digital Model, Digital Shadow, and Digital Twin

D. Proposed Solution and Key Contributions

Although several digital twin applications have been introduced in healthcare, most of them focus on a single organ, a specific medical device, or an isolated hospital department. Such point-level solutions are useful for local analysis, but they do not provide a complete view of how clinical activities, operational workflows, and physical infrastructure interact across the entire hospital. In practice, many systems described as digital twins behave more like static digital replicas or one-way monitoring platforms, where data is collected from the physical environment but is not semantically connected or used for continuous bidirectional reasoning.

A major challenge behind this limitation is the absence of true semantic interoperability. Existing healthcare standards, particularly HL7 FHIR, are highly effective for exchanging structured healthcare information through standardized APIs. However, they do not inherently establish meaningful relationships between clinical entities, building layouts, IoT sensor observations, medical equipment, and staff workflows. As a result, hospitals continue to operate with fragmented information systems that are difficult to integrate into a unified intelligent platform.

To address this research gap, this work proposes the Ontologically Integrated Digital Twin (OIDT) framework. The central idea of OIDT is to represent the hospital's physical, cyber, and organizational components within a single semantic knowledge model called HospitalOnt, developed using the Web Ontology Language (OWL). Instead of treating clinical data, sensor data, and infrastructure data as separate silos, HospitalOnt creates explicit machine-understandable relationships among patients, clinicians, medical devices, rooms, environmental sensors, workflows, and facility resources.

The ontology combines established domain standards to ensure interoperability and extensibility. Clinical concepts are aligned with SNOMED CT, laboratory measurements with LOINC, medication information with RxNorm, healthcare information exchange with HL7 FHIR, and sensor observations with the W3C SSN/SOSA ontologies. By integrating these standards into a unified knowledge graph, OIDT provides a semantic foundation that supports cross-domain reasoning, contextual analytics, and intelligent decision support. The main contributions of this work are summarized below.

Hospital-Wide Digital Twin Architecture. A scalable five-layer architecture is developed to support real-time synchronization between the physical hospital and its virtual counterpart. The architecture integrates the Physical Layer, Data Integration Layer, Ontology and Knowledge Layer, Analytics and Simulation Layer, and Visualization and Interaction Layer, enabling continuous bidirectional communication between sensing, reasoning, prediction, and user interaction components.

Formal Semantic Model: HospitalOnt. An expressive OWL-based ontology is designed to unify clinical, operational, sensor, and infrastructure domains within a single semantic framework. The model extends and connects existing standards such as SNOMED CT, LOINC, W3C

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SSN/SOSA, FOAF, and HL7 FHIR, allowing heterogeneous hospital data to be represented in a consistent and machine-interpretable manner.

Real-Time Distributed Data Pipeline. A high-throughput streaming pipeline is implemented using Apache Kafka and Apache Flink. The pipeline performs real-time ingestion, semantic annotation, event processing, and routing of multi-modal data into specialized storage systems, including Neo4j for graph knowledge representation, InfluxDB for time-series telemetry, and PostgreSQL for transactional healthcare data.

Hybrid AI and Semantic Analytics. Advanced predictive models are integrated directly with the semantically enriched knowledge graph. An LSTM Autoencoder is employed for unsupervised anomaly detection and predictive maintenance of critical medical equipment, while a Prophet-based forecasting model is used to estimate patient arrivals, bed occupancy, and hospital-wide flow patterns. This combination of semantic reasoning and machine learning enables more context-aware and actionable predictions.

Experimental Validation in a Smart Hospital Testbed. The proposed framework is evaluated in a simulated 200-bed smart hospital environment incorporating 50 Raspberry Pi edge nodes, synthetic HL7 FHIR event streams, and heterogeneous IoMT telemetry. The experiments cover five practical scenarios: patient flow optimization, ventilator predictive maintenance, emergency alert routing, disaster evacuation support, and facility energy management, demonstrating measurable operational benefits.

Comprehensive Performance Evaluation. Extensive benchmarks are conducted to evaluate end-to-end latency, semantic query effectiveness, and scalability under increasing IoT workloads. The study includes experiments with up to 10,000 concurrent device streams and presents mathematical formulations for graph-based reasoning, anomaly detection, and energy optimization, providing both architectural and analytical validation of the proposed OIDT framework.

Overall, the proposed OIDT framework moves beyond isolated digital twin applications and establishes a unified semantic and analytical infrastructure for next-generation smart hospitals. By combining ontology-driven interoperability, real-time streaming, graph-based reasoning, and AI-powered prediction, the framework offers a practical foundation for resilient, efficient, and context-aware Healthcare 5.0 environments.

II. BACKGROUND AND RELATED WORK

A. Literature Review and Research Taxonomy

The concept of digital twins in healthcare has evolved through the convergence of several research domains, including industrial IoT, cyber-physical systems, semantic web technologies, artificial intelligence, and health informatics. Although the term digital twin is increasingly used in healthcare literature, existing implementations vary significantly in scope, level of intelligence, and degree of integration with real hospital operations. A careful review of prior work shows that most studies can be grouped into three major categories, each addressing only a limited portion of the broader hospital ecosystem.

1) Patient-Specific Physiological Twins

The first and most mature category focuses on creating digital representations of individual patients, organs, or physiological processes. Researchers have developed highly detailed computational models of the heart, lungs, brain, and other biological systems to support diagnosis, treatment planning, and personalized medicine. Cardiac digital twins, for example, can simulate electrical conduction, tissue deformation, and blood-flow dynamics to assist in the analysis of arrhythmias and the planning of interventions such as catheter ablation. Similar approaches have been explored for cancer progression, glucose metabolism, and pharmacokinetic modeling, where virtual simulations help optimize patient-specific therapies.

These models provide excellent biological and physiological fidelity. However, their scope is usually restricted to the patient or organ level. They are rarely connected to hospital workflows, staffing conditions, equipment availability, environmental factors, or facility operations. As a result, they offer deep insight into individual physiology but do not contribute to hospital-wide situational awareness or operational intelligence.

2) Departmental and Operational Digital Twins

The second stream of research applies digital twin concepts to specific hospital departments or operational processes. Most of these studies rely on Discrete-Event Simulation (DES), system dynamics, or queueing models to analyze workflows such as emergency department triage, operating room scheduling, bed management, and outpatient clinic throughput. These tools are valuable for identifying bottlenecks, evaluating alternative scheduling policies, and performing retrospective what-if analyses.

Despite their usefulness for operational planning, these models generally lack continuous synchronization with live clinical and physical data streams. They are often executed offline using historical datasets, and updates require manual reconfiguration. Consequently, they behave more like simulation environments or digital shadows than true adaptive digital twins capable of responding dynamically to changing hospital conditions.

3) Smart Building and Infrastructure Twins

The third category originates from the domains of civil engineering, facility management, and smart buildings. These systems combine Building Information Modeling (BIM) with telemetry protocols such as BACnet, Modbus, and IoT sensor networks to monitor and optimize HVAC

International Journal of Engineering Research & Technology (IJERT)
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systems, lighting, energy consumption, occupancy, and asset management. In large healthcare facilities, such infrastructure twins can improve energy efficiency and support predictive maintenance of building equipment.

However, these platforms are typically disconnected from clinical information systems. They have little or no semantic understanding of patient conditions, medical device states, clinical workflows, or healthcare events. A temperature anomaly in an intensive care unit, for instance, may be detected as a facility issue, but the system is generally unable to relate that event to the condition of critically ill patients or the operation of life-support equipment.

Research Gap

The literature therefore reveals a fragmented landscape. Physiological twins provide deep clinical detail, operational twins provide workflow analysis, and infrastructure twins provide facility optimization, but none of them offers a unified representation that integrates clinical, operational, and infrastructural domains within a common semantic framework. Existing interoperability standards such as HL7 FHIR enable structured data exchange, yet they do not inherently establish semantic relationships between patients, medical devices, rooms, sensors, staff activities, and building resources.

This lack of cross-domain semantic integration is the primary barrier to realizing a truly hospital-wide digital twin. Without a shared knowledge model, data remains distributed across heterogeneous systems, limiting contextual reasoning, predictive analytics, and coordinated decision support.

To clarify this research landscape, Table I compares representative healthcare digital twin categories and state-of-the-art frameworks with the proposed Ontologically Integrated Digital Twin (OIDT) framework, highlighting differences in semantic interoperability, real-time synchronization, cross-domain reasoning, and hospital-wide intelligence.

TABLE I COMPARATIVE TAXONOMY OF DIGITAL TWIN FRAMEWORKS IN HEALTHCARE

Literature	Scope	Semantic Model	Real-Time Sync	Data Integration Domain	Primary Bottleneck / Gap
Tao et al. [2]	Industrial DT	5-D Conceptual Model	Yes	Physical and cyber systems	Not healthcare-specific; lacks clinical terminologies and hospital semantics
Fuller et al. [3]	Generic DT	Conceptual	Yes	Multi-sensor fusion	No formal ontology or semantic reasoning layer
Wang et al. [4]	Healthcare Knowledge Graph	Graph ontology	No (batch processing)	Clinical EHR data only	Excludes IoT telemetry, building systems, and operational assets
Physiological Twins (e.g., virtual heart)	Patient / organ	Biophysical equations	Yes	Clinical vitals and genomics	Limited to a single organ or patient; no operational or infrastructure context
Operational Twins (e.g., ED simulators)	Departmental	Queueing / DES models	No (simulated)	Process workflows	Offline analysis; lacks real-time streaming and device integration
Smart Building Twins (e.g., BMS systems)	Facility / HVAC	BIM / BACnet	Yes	Environmental telemetry	No clinical awareness, patient context, or medical device integration
Proposed OIDT Framework [1]	Hospital-wide	OWL ontology (HospitalOnt)	Yes (bidirectional)	Clinical, operational, and physical infrastructure data	Integrated semantic framework unifying all hospital domains

B. Semantic Interoperability and Standard Vocabularies

Achieving true semantic interoperability—the ability of systems not only to exchange data but also to interpret that data with the same meaning—is one of the most significant challenges in modern healthcare integration. In many hospitals, information flows across Electronic Health Records (EHRs), laboratory systems, medical devices, IoT sensors, and facility management platforms. Although these systems may communicate syntactically, they often lack a shared semantic understanding, which prevents meaningful cross-domain reasoning and coordinated decision support.

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It is important to distinguish between syntactic interoperability and semantic interoperability. Syntactic standards define how data is structured and transported, such as XML or JSON formats and communication mechanisms including RESTful HTTP, WebSockets, or MQTT. Semantic standards, in contrast, define the concepts, relationships, and contextual meaning of the data being exchanged. Without this semantic layer, systems can transmit information successfully while still failing to understand how that information relates to patients, devices, locations, workflows, and infrastructure.

Several well-established healthcare vocabularies address specific subdomains of the problem.

- HL7 FHIR (Fast Healthcare Interoperability Resources): FHIR defines standardized clinical and administrative entities as modular Resources such as Patient, Observation, Device, Encounter, and Location, which can be accessed through RESTful APIs. FHIR has greatly simplified interoperability between healthcare applications; however, it is primarily a data-exchange standard and does not provide rich ontological reasoning or expressive semantic inference capabilities.
- SNOMED CT (Systematized Nomenclature of Medicine—Clinical Terms): SNOMED CT is a comprehensive clinical terminology containing more than 350,000 active concepts organized in formal hierarchies. Its ontological structure supports consistent representation of diseases, findings, procedures, body structures, and clinical relationships, making it a powerful foundation for semantic clinical modeling.
- LOINC (Logical Observation Identifiers Names and Codes): LOINC standardizes laboratory tests and clinical observations, enabling consistent representation of measurements such as serum potassium, oxygen saturation, blood glucose, and continuous heart-rate monitoring.
- RxNorm: RxNorm provides normalized identifiers and names for medications and establishes mappings across multiple drug vocabularies, supporting consistent medication interoperability.
- W3C SSN/SOSA (Semantic Sensor Network / Sensor, Observation, Sample, and Actuator): This W3C ontology models physical sensors, observations, actuators, and sampling procedures, making it particularly suitable for representing IoMT devices, environmental sensors, and smart-building telemetry.

While each of these standards is highly valuable within its respective domain, they do not by themselves create a unified semantic model of the hospital environment. Prior research has shown that the main interoperability gap lies in connecting clinical meaning with physical context and operational state.

For example, SNOMED CT can accurately represent the clinical concept Hypoxia (Concept ID: 40930008). FHIR can represent the patient and the associated observation. SSN/SOSA can represent sensor measurements. However, none of these standards alone can naturally express a composite situation such as:

- the patient experiencing hypoxia is located in Bed B of Room 301,
- the patient is connected to Ventilator V-102,
- the ventilator is showing an abnormal filter pressure drop,
- the room belongs to HVAC Zone 4,
- and a maintenance alert has been issued for that ventilation zone.

Understanding this situation requires linking clinical, spatial, device, environmental, and operational information into a single machine-interpretable context.

The HospitalOnt ontology proposed in this work addresses precisely this gap. HospitalOnt acts as a semantic integration layer that connects FHIR resources, SNOMED CT concepts, LOINC observations, RxNorm medications, and SSN/SOSA sensor entities within a unified OWL-based knowledge graph. By explicitly modeling relationships among patients, clinicians, medical devices, rooms, sensors, workflows, and facility infrastructure, the ontology enables cross-domain reasoning that is not achievable with any individual standard alone.

This integrated semantic foundation allows the digital twin to answer complex contextual queries, support predictive analytics, and generate intelligent operational insights. Rather than treating clinical systems, IoT platforms, and building management systems as isolated silos, HospitalOnt transforms them into a coordinated and semantically coherent representation of the hospital as a living cyber-physical ecosystem.

III. FRAMEWORK SCOPE AND RESEARCH GAP

A. Research Gap Analysis

A detailed review of the existing literature, commercial healthcare platforms, and enterprise health IT architectures reveals that the current generation of healthcare digital twins still falls short of supporting a truly integrated, hospital-wide intelligent environment. Although significant progress has been made in areas such as EHR interoperability, IoMT monitoring, workflow analytics, and smart-building management, these capabilities remain fragmented across independent systems. Based on this analysis, five major research gaps are identified.

Semantic Interoperability Gap. The most critical limitation is the absence of a unified semantic model capable of connecting clinical, operational, and infrastructural information. Electronic Health Records, IoMT devices, staff-

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
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management systems, and Building Management Systems are typically implemented using different data models and domain vocabularies. Even when standards such as HL7 FHIR are adopted, they primarily support data exchange rather than cross-domain reasoning. As a result, hospitals cannot easily infer relationships between a patient's clinical condition, the status of the medical devices attached to that patient, the availability of clinical staff, and the environmental state of the surrounding infrastructure. This fragmentation significantly restricts contextual awareness and coordinated decision-making.

Isolation of Predictive AI Models. A second gap lies in the way predictive analytics is commonly deployed in healthcare. Most machine-learning models are trained on historical and relatively static database snapshots. Once deployed, these models often operate independently of the continuously evolving clinical and operational context. For example, a device-failure model may analyze sensor values without considering patient acuity, room conditions, maintenance history, or workload patterns. The lack of integration with dynamic knowledge graphs reduces explainability, increases false-positive alerts, and limits the ability of clinicians and engineers to trust and interpret AI-generated predictions.

Limitations of Unidirectional Data Flow. Many existing hospital dashboards and monitoring platforms behave as digital shadows rather than true digital twins. They collect and visualize telemetry from medical devices, information systems, or facility sensors, but the flow of information is largely one-way. The virtual representation observes the physical environment without influencing it. Consequently, these systems provide situational awareness but do not support closed-loop decision-making, automated workflow adaptation, or context-aware feedback to operational processes such as alert routing, bed allocation, equipment dispatch, or energy control.

Scalability–Expressiveness Bottleneck. Semantic technologies offer rich reasoning capabilities, yet they introduce significant computational challenges when applied to real-time IoT environments. Expressive OWL-DL reasoning can become computationally expensive, with worst-case complexity reaching 2NEXPTIME. Executing such reasoning directly on high-frequency sensor streams is impractical for large hospitals generating thousands of events per second. Existing architectures often choose either semantic expressiveness or streaming scalability, but rarely achieve both simultaneously. There is a clear need for architectures that combine lightweight real-time stream processing with selective, context-aware ontological reasoning.

Lack of Unified Hospital-Wide Validation. Finally, empirical validation remains limited. A substantial portion of the digital twin literature presents conceptual frameworks, small laboratory prototypes, or department-specific case studies. Few studies provide quantitative evaluation across multiple hospital dimensions simultaneously, such as clinical performance, operational efficiency, emergency response, and energy management. Without integrated validation in a realistic hospital-scale environment, it is difficult to assess whether proposed frameworks can deliver measurable benefits in real-world Healthcare 5.0 settings.

Taken together, these gaps demonstrate that the challenge is not merely the creation of another digital model of a hospital. The unresolved problem is the development of a semantically integrated, context-aware, scalable, and empirically validated digital twin capable of synchronizing clinical, operational, and infrastructural intelligence in real time. The proposed Ontologically Integrated Digital Twin (OIDT) framework is designed specifically to address these five limitations through ontology-driven interoperability, hybrid stream-and-graph processing, context-enriched AI analytics, bidirectional synchronization, and hospital-scale experimental validation.

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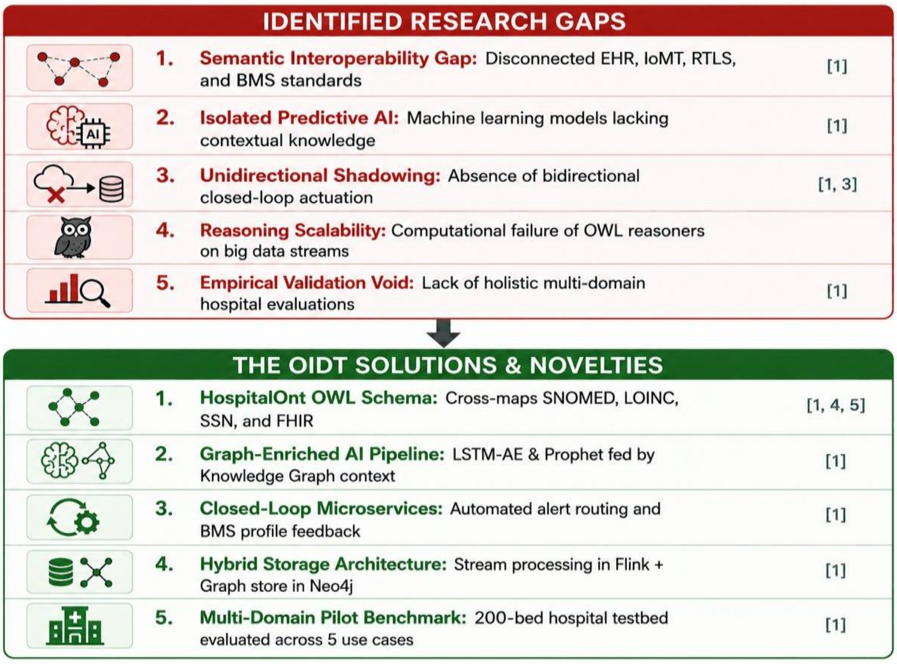

Fig. 3. Identified Research Gaps and Corresponding OIDT Solutions and Novel Contributions

B. Formal Research Questions

To address the research gaps identified in the previous section, this study formulates three core research questions that guide the design, implementation, and evaluation of the proposed Ontologically Integrated Digital Twin (OIDT) framework. These questions focus on the architectural, semantic, and predictive dimensions of a hospital-wide digital twin.

RQ1: Real-Time Multi-Modal Integration

How can a distributed and layered architecture be designed to ingest, process, and semantically integrate heterogeneous real-time data streams from IoMT devices, FHIR-based EHR systems, RTLS trackers, and building-management infrastructure while maintaining an end-to-end latency of less than three seconds?

This question investigates the feasibility of combining high-throughput streaming technologies with semantic integration mechanisms in a large-scale healthcare environment. The goal is not only to transport data efficiently, but also to preserve temporal consistency, contextual relationships, and interoperability across clinical, operational, and infrastructural systems. Particular attention is given to the interaction between edge processing, stream analytics, semantic annotation, and multi-model data persistence.

RQ2: Effectiveness of Ontology-Driven Integration

To what extent does the formal multi-domain ontology, HospitalOnt, improve cross-domain query resolution and semantic reasoning when compared with conventional siloed database architectures?

This question evaluates the semantic contribution of the proposed ontology. Traditional hospital systems store information in independent relational structures, making it difficult to answer queries that span patients, devices, locations, workflows, and facility resources. The study examines whether the OWL-based HospitalOnt model can provide more complete, context-aware, and machine-interpretable query results, thereby enabling richer reasoning and improved interoperability across previously disconnected domains.

RQ3: Predictive Intelligence and Operational Impact

How accurately can predictive machine-learning models operating on semantically enriched graph data forecast operational bottlenecks, such as patient-flow congestion, and physical asset failures, such as ventilator degradation, and what measurable operational and environmental benefits can be achieved?

This question focuses on the practical value of combining semantic knowledge graphs with AI analytics. The study evaluates whether context-enriched graph representations improve predictive performance, explainability, and decision support compared with models trained on isolated tabular datasets. In addition to prediction accuracy, the research measures real-world impact through indicators such as waiting-time reduction, maintenance lead time, emergency-response improvement, and energy-efficiency gains.

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Together, these research questions establish a structured evaluation framework for OIDT, linking system architecture (RQ1), semantic interoperability (RQ2), and predictive operational intelligence (RQ3). This progression allows the study to assess not only whether a hospital-wide semantic digital twin can be built, but also whether it delivers measurable improvements in healthcare operations, infrastructure management, and intelligent decision support.

IV. SYSTEM ARCHITECTURE

The proposed Ontologically Integrated Digital Twin (OIDT) is organized as a five-layer architecture designed to support continuous synchronization between the physical hospital environment and its virtual, semantically enriched counterpart. The layered design separates sensing, integration, knowledge representation, analytics, and interaction responsibilities while maintaining tightly coupled communication among all components. This modular organization improves scalability, fault isolation, maintainability, and the ability to integrate future healthcare technologies without redesigning the entire platform.

At the lowest level, the architecture captures real-time data from clinical devices, environmental sensors, operational systems, and building infrastructure. These heterogeneous streams are processed through a distributed integration layer that performs ingestion, temporal synchronization, and semantic annotation. The annotated data is then transformed into a unified knowledge graph within the ontology layer, where relationships among patients, devices, locations, workflows, and facility resources are explicitly represented. On top of this semantic foundation, advanced analytics and simulation services generate predictions, detect anomalies, evaluate operational scenarios, and support intelligent decision-making. Finally, the visualization and interaction layer provides clinicians, administrators, and facility engineers with real-time dashboards, alerts, simulations, and bidirectional control interfaces.

Unlike conventional hospital monitoring platforms, which typically provide isolated views of either clinical data or facility telemetry, the OIDT architecture is designed to function as a hospital-wide cyber-physical intelligence platform. Information flows not only from the physical environment to the digital twin, but also from the digital twin back to operational workflows through recommendations, alerts, and automated control actions. This bidirectional synchronization is a defining characteristic of the proposed framework.

The five functional layers are:

- Physical Sensing Layer – acquisition of data from IoMT devices, EHR systems, RTLS infrastructure, and building sensors.
- Data Integration Layer – real-time ingestion, streaming, semantic annotation, and multi-model data routing.
- Ontology and Knowledge Layer – OWL-based semantic representation and graph-based contextual reasoning.
- Analytics and Simulation Layer – AI prediction, anomaly detection, forecasting, and discrete-event simulation.
- Visualization and Interaction Layer – dashboards, alerts, digital twin interfaces, and closed-loop operational feedback.

The overall architectural layout and the interactions among these layers are illustrated in Figure 4, which shows the end-to-end flow from physical sensing to semantic reasoning and intelligent decision support.

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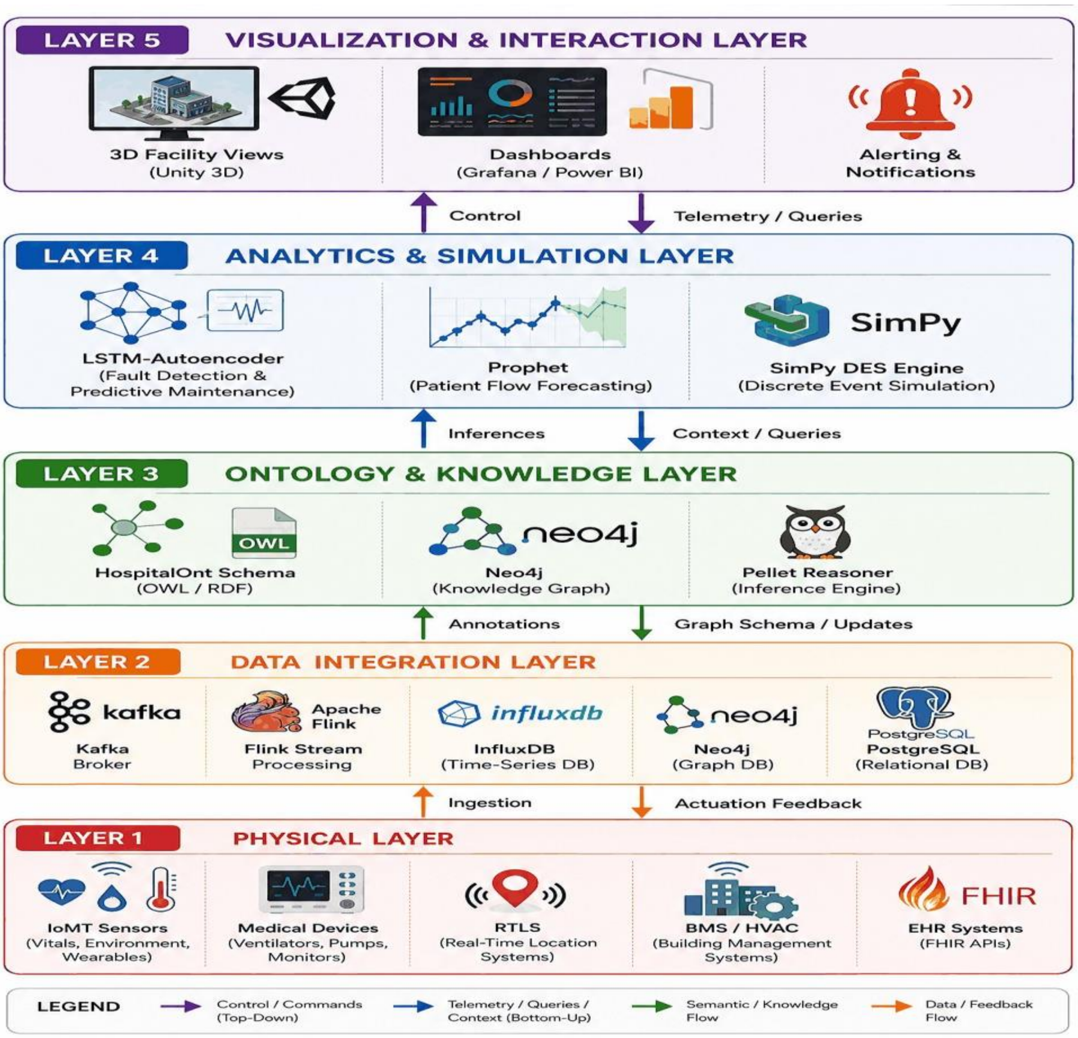

Fig. 4. Five-Layer OIDT System Architecture. Arrows indicate bidirectional data and control flow between adjacent layers.

A. Layer 1: Physical Layer

The Physical Layer forms the foundation of the proposed OIDT architecture and represents the real-world hospital environment from which all operational intelligence originates. It includes every tangible entity capable of generating data, receiving commands, or participating in clinical, operational, or infrastructural processes. This layer therefore encompasses not only patients and medical devices, but also staff, rooms, environmental sensors, and facility-management equipment.

In a modern smart hospital, these physical entities continuously produce heterogeneous data streams with different frequencies, formats, and reliability characteristics. Physiological monitors may transmit data every second, infusion pumps may report status changes intermittently, RTLS trackers may update location every few seconds, and building systems may publish environmental measurements at longer intervals. The Physical Layer is responsible for exposing these diverse signals to the higher layers of the digital twin while preserving their temporal and contextual information.

The layer can be grouped into four major categories:

- Clinical entities: patients, bedside monitors, ventilators, infusion pumps, and other medical equipment.
- Operational entities: clinicians, nursing staff, transport teams, and RTLS tracking devices.
- Environmental entities: temperature, humidity, air-quality, occupancy, and lighting sensors.
- Infrastructure entities: HVAC units, power systems, elevators, and other Building Management System (BMS) components.

Each entity is associated with a unique semantic identity that is later linked to the HospitalOnt knowledge graph. This semantic binding allows a physical event—such as a ventilator pressure anomaly or a room temperature deviation—to be interpreted in relation to the patient, location, workflow, and infrastructure context in which it occurs.

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The Physical Layer supports both data acquisition and actuation. Upstream communication carries telemetry from devices and sensors to the digital twin, while downstream communication enables operational actions such as alert routing, equipment dispatch, environmental control adjustments, or workflow recommendations. This bidirectional capability distinguishes the architecture from traditional monitoring systems that only collect and display data.

To ensure interoperability, the layer uses standard healthcare and IoT communication mechanisms, including HL7 FHIR, MQTT, BACnet, Modbus, and vendor-specific device interfaces where required. Edge gateways normalize these heterogeneous protocols before forwarding data to the integration layer.

Table II summarizes the primary physical-layer entities, the types of data they generate, their typical acquisition frequencies, communication protocols, and their semantic bindings within the HospitalOnt ontology. This mapping establishes the foundation for real-time contextual reasoning across clinical, operational, and infrastructural domains.

TABLE II DATA SOURCES, SPECIFICATIONS, AND SEMANTIC CLASS MAPPINGS

Source / Entity	Data Type / Payload	Freq.	Protocol	Target Semantic Class (HospitalOnt)
ECG Bedside Monitor	Waveform and numeric physiological stream	250 Hz	MQTT over TLS	sosa:Observation, HospitalOnt:VitalSign
Infusion Pump	Flow rate, device status, alarm events	1 Hz	MQTT / Zigbee	sosa:Observation, HospitalOnt:MedicationAdministration
Smart Hospital Bed	Occupancy, patient weight, bed angle	0.1 Hz	MQTT	sosa:Observation, HospitalOnt:BedState
EHR / LIS	Laboratory results, encounters, clinical events	Event-driven	RESTful HL7 FHIR	fhir:Observation, fhir:Patient
BMS / HVAC	Temperature, airflow, pressure	0.01 Hz	BACnet/IP	sosa:Observation, HospitalOnt:EnvironmentalParameter
RTLS Badges / Tags	X, Y, Z coordinates, zone transitions	1 Hz	Wi-Fi / BLE	HospitalOnt:LocationObservation

B. Layer 2: Data Integration Layer

The Data Integration Layer acts as the communication and processing backbone of the OIDT framework. Its primary responsibility is to transform heterogeneous raw data generated by the Physical Layer into semantically enriched, time-synchronized, and analytically usable information. This layer bridges the gap between high-frequency device telemetry, event-driven clinical records, operational location updates, and building-management data, ensuring that all streams can be processed consistently within a unified digital twin environment.

In a hospital-scale deployment, data arrives continuously from thousands of distributed sources using different protocols, payload formats, and update rates. The integration layer therefore performs four tightly coupled functions: message ingestion, stream processing, semantic annotation, and multi-model persistence.

1) Message Ingestion

Incoming data is first collected through protocol-specific connectors and edge gateways. IoMT devices communicate primarily through MQTT over TLS, EHR and laboratory systems expose HL7 FHIR RESTful APIs, RTLS infrastructure provides Wi-Fi/BLE location events, and building systems publish telemetry through BACnet/IP or Modbus interfaces. All incoming events are normalized into a common internal event format and forwarded to the distributed streaming backbone.

2) High-Throughput Stream Processing

The streaming backbone is implemented using Apache Kafka and Apache Flink. Kafka provides durable, partitioned event streams that support horizontal scalability and fault tolerance, while Flink performs real-time event processing with low latency. Processing operations include temporal ordering, deduplication, missing-value handling, sliding-window aggregation, anomaly pre-filtering, and synchronization of multi-source events. This design allows the system to process both high-frequency physiological streams and lower-frequency operational or environmental updates within the same pipeline.

3) Semantic Annotation

A key feature of the OIDT architecture is that semantic enrichment occurs during stream processing rather than as a later offline step. Each event is mapped to its corresponding HospitalOnt class and linked with contextual entities such as patient, device, room, zone, clinician, or workflow. For example, a heart-rate observation from an ECG monitor is not stored merely as a numeric value; it is annotated as a sosa:Observation associated with a specific patient encounter, device, and physical location. This enrichment enables downstream reasoning, cross-domain queries, and context-aware analytics.

4) Multi-Model Persistence

After semantic processing, data is routed to specialized storage systems according to its access pattern and analytical purpose:

- Neo4j stores semantic relationships and contextual knowledge graphs.
- InfluxDB stores high-frequency time-series telemetry.
- PostgreSQL stores transactional and structured healthcare records.

This multi-model approach avoids forcing all data into a single storage paradigm and significantly improves both query performance and scalability.

The Data Integration Layer is designed to support near real-time bidirectional synchronization. In addition to ingesting data from the physical environment, it can also propagate alerts, recommendations, and control actions generated by higher layers back to operational systems and devices.

The overall streaming workflow—from protocol ingestion through Kafka buffering, Flink-based processing, semantic enrichment, and persistence into graph, time-series, and relational databases—is illustrated in Figure 5, which depicts the detailed event-processing pipeline of the proposed OIDT framework.

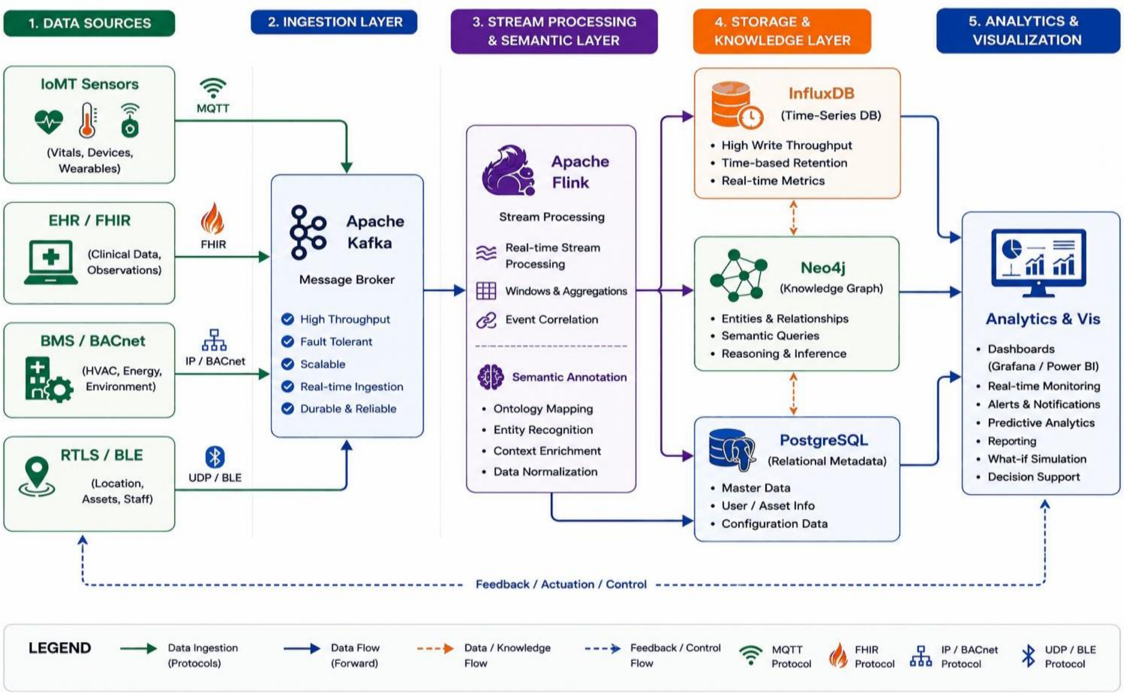

Fig. 5. Real-Time Hospital Data Integration and Semantic Processing Pipeline

Apache Kafka Messaging Backbone

At the core of the integration layer is Apache Kafka, which serves as a fault-tolerant and horizontally scalable event-streaming backbone. Data arriving from MQTT gateways, BACnet adapters, FHIR webhooks, and RTLS collectors is published to domain-oriented Kafka topics such as telemetry.vitals, telemetry.bms, events.fhir, and rtls.locations. Topic partitioning enables parallel consumption, while Kafka's persistent log architecture ensures durability and recovery in the event of node or network failures. This decouples data producers from downstream processing services and allows the architecture to scale independently across acquisition, processing, and analytics components.

Apache Flink Stream Processing and Semantic Enrichment

Incoming events are consumed by Apache Flink, which performs stateful real-time processing with millisecond-level event management. Flink executes temporal ordering, sliding-window aggregation, filtering, anomaly preprocessing, and stream joins. A distinguishing feature of the OIDT pipeline is that semantic enrichment is performed during stream processing rather than as a separate offline operation.

When a telemetry frame is received, Flink joins the incoming device identifier with static metadata cached from PostgreSQL, including device type, patient assignment, room location, and semantic class mappings. The processor then generates RDF-aligned semantic annotations consistent with

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HospitalOnt. For example, an ECG value is transformed from a raw numeric measurement into a semantically contextualized observation linked to the patient, monitoring device, encounter, and physical location. This approach ensures that downstream analytics operates on context-rich graph-connected data rather than isolated sensor values.

Polyglot Persistence Layer

After semantic processing, events are routed to a polyglot persistence layer, where each database is selected according to its query and performance characteristics.

InfluxDB – Time-Series Persistence: InfluxDB is optimized for high-volume, write-intensive telemetry workloads. It stores continuous numeric streams such as ECG waveforms, heart rate, oxygen saturation, temperature, airflow, and other sensor measurements. Its compression, retention policies, and efficient temporal indexing make it well suited for large-scale physiological and environmental data.

Neo4j – Knowledge Graph Persistence: Neo4j stores the live instances of the HospitalOnt knowledge graph. Nodes represent entities such as patients, devices, rooms, clinicians, and sensors, while edges capture their semantic relationships. This structure enables fast traversal and contextual Cypher queries across connected hospital topologies, supporting real-time reasoning and cross-domain analytics.

PostgreSQL – Transactional Persistence: PostgreSQL maintains structured transactional data, including device metadata, room assignments, user accounts, access-control policies, configuration parameters, and audit records. It provides strong relational consistency for operational management functions that are not naturally represented as time-series or graph data.

Together, Kafka, Flink, and the polyglot persistence layer create a distributed integration architecture that combines stream scalability, semantic expressiveness, and storage specialization. This design allows the OIDT framework to continuously synchronize clinical, operational, and infrastructural data streams while maintaining the low-latency performance required for hospital-wide digital-twin applications.

V. ONTOLOGY DESIGN AND IMPLEMENTATION

A. HospitalOnt Architecture

The semantic foundation of the proposed OIDT framework is the HospitalOnt ontology, which provides a unified and machine-interpretable representation of the hospital ecosystem. The ontology was developed using Protégé 5.5 and engineered according to the Methontology methodology, which emphasizes systematic specification, conceptualization, formalization, implementation, and validation of ontological models. This disciplined approach was adopted to ensure consistency, extensibility, and interoperability with established healthcare and IoT standards.

Within the OIDT architecture, HospitalOnt serves as the core semantic schema for the Neo4j knowledge graph. Rather than storing isolated data records, the ontology models the hospital as a network of interconnected entities and relationships. Every patient, device, room, clinician, sensor, workflow, and infrastructure component is represented as a semantic entity that can participate in logical reasoning and graph-based traversal.

The ontology is organized around four tightly integrated domains:

- Clinical Domain – patients, encounters, observations, diagnoses, procedures, medications, and laboratory results.
- Device and IoMT Domain – medical devices, sensors, actuators, telemetry streams, and device states.
- Infrastructure and Facility Domain – rooms, beds, wards, HVAC zones, environmental parameters, and building assets.
- Personnel and Operational Domain – clinicians, nurses, technicians, teams, roles, schedules, tasks, and workflow events.

A key design objective was to avoid creating a completely new vocabulary. Instead, HospitalOnt acts as a semantic integration layer that reuses and aligns widely accepted standards, including HL7 FHIR, SNOMED CT, LOINC, RxNorm, W3C SSN/SOSA, and FOAF. This alignment enables external healthcare systems to exchange data while preserving semantic meaning within the digital twin.

The ontology follows a modular architecture in which each domain is implemented as a reusable sub-ontology connected through shared upper-level concepts such as Person, Device, Location, Observation, and Event. This modularization improves maintainability and allows future extensions, such as surgical robotics, pharmacy automation, or population-health analytics, to be incorporated without restructuring the existing model.

In the Neo4j implementation, OWL classes are mapped to graph node labels, object properties become semantic relationships, and selected data properties are indexed as graph attributes. This hybrid OWL-to-property-graph approach preserves semantic expressiveness while enabling efficient real-time graph queries required by operational digital-twin applications.

The ontology is designed to support several categories of reasoning:

- Contextual reasoning (e.g., identifying all devices associated with a critically ill patient),
- Spatial reasoning (e.g., locating patients within affected HVAC zones),

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ISSN: 2278-0181
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- Operational reasoning (e.g., determining the responsible care team for an alert),
- Temporal reasoning (e.g., correlating clinical deterioration with environmental changes), and
- Asset reasoning (e.g., linking maintenance history with device anomalies).

To illustrate the structure of the ontology, Figure 6 presents a representative subgraph of the HospitalOnt schema, showing how entities from the clinical, device, infrastructure, and personnel domains are interconnected within a single semantic graph. This interconnected structure forms the basis for cross-domain querying, graph analytics, and context-aware decision support throughout the OIDT framework.

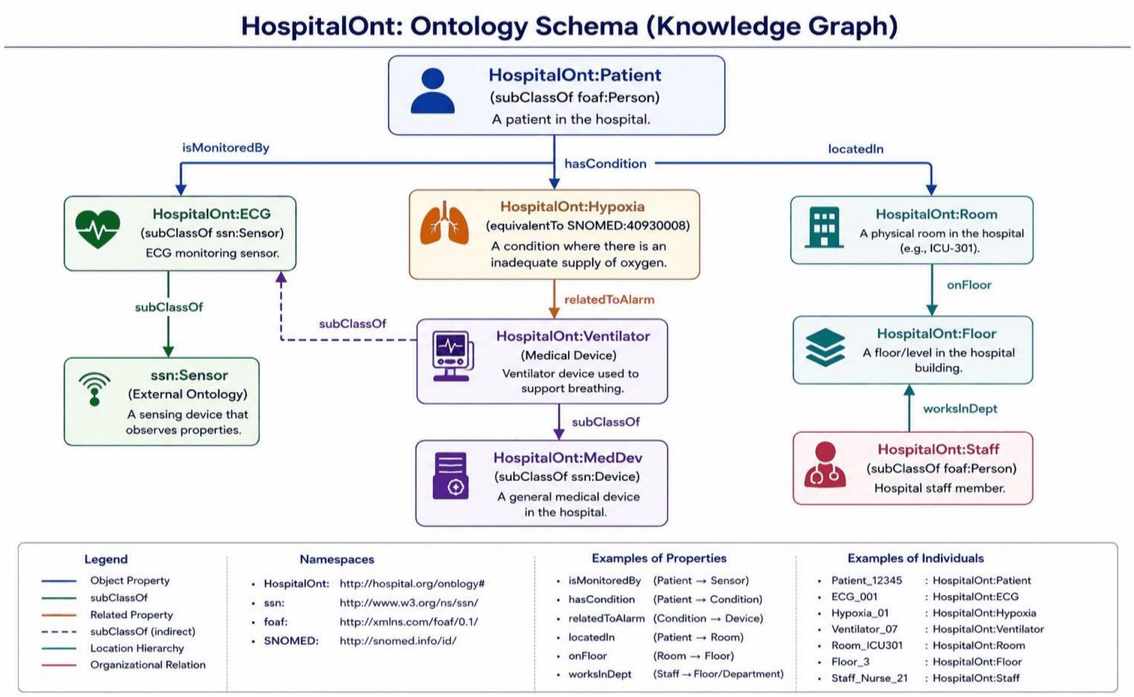

Fig. 6. HospitalOnt Ontology Schema and Knowledge Graph Relationships

B. Formal Ontology Specification

The HospitalOnt ontology is formally defined using the Description Logic SROIQ(D), which forms the logical foundation of OWL 2 DL. This level of expressiveness was selected because it supports class hierarchies, property restrictions, existential quantification, role composition, and data properties while remaining compatible with standard semantic-web reasoning tools.

Patient Modeling

A patient is modeled as a specialization of the FOAF Person concept and is required to be associated with at least one FHIR-based medical record:

$$Patient \sqsubseteq foaf{:}Person \sqcap \exists hasMedicalRecord.FHIR{:}PatientRecord$$

This axiom ensures that every instance classified as a Patient is both a person and semantically linked to a structured clinical record represented using FHIR resources.

Medical Device Modeling

A ventilator is represented as a specialized medical device equipped with both airflow and pressure sensing capabilities:

$$Ventilator \sqsubseteq MedicalDevice \sqcap \exists hasSensor.AirflowSensor \sqcap \exists hasSensor.PressureSensor$$

This definition captures the structural composition of the device and allows reasoning engines to infer that any device possessing the required sensor configuration belongs to the Ventilator class.

Clinical–Device Contextual Inference

One of the key advantages of HospitalOnt is its ability to express clinically meaningful contextual situations. The following equivalence axiom defines a Critical Hypoxic Patient:

$$CriticalHypoxicPatient \equiv Patient \sqcap \exists hasCondition.Hypoxia \sqcap \exists monitoredBy.(Ventilator \sqcap \exists hasState.FaultyState)$$

This expression states that an individual is inferred to be a CriticalHypoxicPatient if: the individual is a patient, the patient has a hypoxic condition, and the patient is monitored by a ventilator that is currently in a faulty state.

Importantly, this class does not need to be asserted manually. It can be inferred automatically by the reasoning engine when the relevant clinical and device facts become available in the knowledge graph.

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In practical terms, if a patient is diagnosed with hypoxia through SNOMED CT-aligned clinical data and the associated ventilator is simultaneously classified as faulty based on real-time sensor telemetry, the ontology can automatically derive that the patient belongs to the CriticalHypoxicPatient class. This inferred classification can then trigger downstream actions such as:

- escalation of clinical alerts,
- prioritization of biomedical maintenance,
- notification of the responsible care team,
- and visualization within the digital twin dashboard.

These axioms demonstrate how HospitalOnt moves beyond simple data integration toward semantic reasoning over combined clinical and operational context. By formally connecting patients, conditions, devices, and infrastructure, the ontology enables the OIDT framework to support machine-interpretable decision support rather than merely storing heterogeneous healthcare data.

Core Object Properties

To support contextual reasoning across clinical, operational, and spatial domains, HospitalOnt defines a set of semantically grounded object properties. Two of the most important relationships are isMonitoredBy and locatedIn, which connect patients, medical devices, staff members, and hospital spaces within a unified graph structure.

Object Property: isMonitoredBy

- Domain: HospitalOnt:Patient
- Range: HospitalOnt:MedicalDevice
- Inverse Property: monitorsPatient

This property represents the clinical monitoring relationship between a patient and a medical device. It enables the ontology to explicitly capture which devices are actively associated with a patient at a given time. Because the property is declared with the inverse relation monitorsPatient, reasoning engines can automatically infer the reciprocal relationship without requiring duplicate assertions.

For example:

Patient_123 isMonitoredBy Ventilator_V102

allows the inference:

Ventilator_V102 monitorsPatient Patient_123

This bidirectional semantic linkage is essential for device-centric alerting, maintenance prioritization, and patient-impact analysis.

Object Property: locatedIn

- Domain: HospitalOnt:Entity (Patient, Staff, MedicalDevice)
- Range: HospitalOnt:SpatialZone (Room, Corridor, Ward)

The locatedIn property models the spatial context of entities within the hospital environment. By defining a common spatial relationship for patients, staff members, and medical devices, the ontology establishes a unified location model that supports cross-domain reasoning. Examples include:

Patient_123 locatedIn Room_301

Nurse_A17 locatedIn Ward_ICU

Ventilator_V102 locatedIn Room_301

Through these assertions, the knowledge graph can infer co-location relationships, identify nearby staff during emergencies, associate devices with patients in the same room, and correlate environmental conditions with clinical events.

The combination of isMonitoredBy and locatedIn enables context-aware semantic reasoning. For instance, if a patient and a ventilator are both located in Room 301 and the ventilator enters a faulty state, the ontology can infer the set of affected patients, responsible staff, and impacted spatial zones. This capability is a key enabler of the hospital-wide situational awareness provided by the OIDT framework.

The isMonitoredBy relationship is implemented in HospitalOnt as an OWL object property that semantically links a patient to the medical device responsible for monitoring that patient. The property is defined with Patient as its domain, MedicalDevice as its range, and monitorsPatient as its inverse property. This inverse declaration enables automatic bidirectional inference by OWL reasoners, allowing device-centric and patient-centric queries to be answered without redundant assertions.

<owl:ObjectProperty rdf:about="http://www.semanticweb.org/ontologies/HospitalOnt#isMonitoredBy">

<rdfs:domain rdf:resource=".../HospitalOnt#Patient"/>

<rdfs:range rdf:resource=".../HospitalOnt#MedicalDevice"/>

<owl:inverseOf rdf:resource=".../HospitalOnt#monitorsPatient"/>

</owl:ObjectProperty>

Semantically, this definition means that whenever the ontology contains the assertion

Patient_123 isMonitoredBy Ventilator_V102

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an OWL reasoner can automatically infer the inverse relationship

Ventilator_V102 monitorsPatient Patient_123

without requiring an explicit additional statement.

This modeling approach is particularly important in the OIDT framework because it supports context-aware reasoning across clinical and operational domains. For example, if a ventilator enters a faulty state, the knowledge graph can immediately identify all patients monitored by that device and propagate alerts to the corresponding care team. Similarly, maintenance queries can be issued from the device perspective, while clinical queries can be issued from the patient perspective, both relying on the same underlying semantic relationship.

By formally defining domains, ranges, and inverse properties, HospitalOnt ensures semantic consistency, reduces data redundancy, and enables efficient graph-based reasoning over patient–device associations in the hospital-wide digital twin.

C. Real-Time Semantic Ingestion Algorithm

Continuous synchronization between high-frequency sensor streams and the Neo4j knowledge graph is performed through Algorithm 1, which is executed within the streaming layer of the OIDT framework. The algorithm combines time-series persistence, contextual graph retrieval, semantic state updates, and rule-based alert triggering in a single low-latency processing pipeline.

The design follows a two-tier persistence strategy. Raw numerical telemetry is first written to InfluxDB, which is optimized for high-frequency continuous data. Only the contextual and clinically relevant state is propagated to the Neo4j knowledge graph, preventing excessive graph growth while preserving semantic connectivity among patients, devices, and locations.

Algorithm 1: Real-Time Semantic Annotation and Knowledge Graph Update

Input : Telemetry Topic T, Payload Message M

Output: Updated Knowledge Graph State, Triggered Rule Actions

```
data <- JSON.parse(M)
sensorID <- T.extractSensorID()
timestamp <- data.timestamp
val <- data.value

// Step 1: Write raw high-frequency numeric value to Time-Series DB
InfluxDB.writePoint(measurement=sensorID, field="val", value=val, time=timestamp)

// Step 2: Query Knowledge Graph for Contextual Bounding
cypherQuery <- "MATCH (s:Sensor {id: $sid})-[:MONITORS]->(p:Patient)
MATCH (p)-[:LOCATED_IN]->(r:Room)
RETURN p.id AS patientID, r.id AS roomID"
context <- Neo4j.execute(cypherQuery, sid=sensorID)

// Step 3: Conditional Graph Update & Rule Trigger
if context.patientID is not NULL then
updateGraph <- "MATCH (p:Patient {id: $pid})
SET p.latestSpO2 = $val, p.lastUpdated = $ts"
Neo4j.execute(updateGraph, pid=context.patientID, val=val, ts=timestamp)

if val < 90.0 then
TriggerClinicalAlert(context.patientID, context.roomID, val)
  end if
end if
```

The algorithm begins by parsing the incoming MQTT or Kafka payload and extracting the sensor identifier, timestamp, and measured value. The raw measurement is immediately persisted to InfluxDB to guarantee durable storage of the complete telemetry stream, including high-frequency observations that are not suitable for full graph materialization.

In the second stage, the system performs a contextual graph lookup using Cypher. Rather than processing the sensor reading in isolation, the query retrieves the patient currently monitored by the sensor and the room in which that patient is located. This operation effectively binds the incoming numeric value to its clinical and spatial context.

If a valid patient association exists, the knowledge graph is updated with the latest semantic state. In the example shown, the patient node stores the most recent oxygen saturation value (latestSpO2) and the corresponding update timestamp. This lightweight graph update allows downstream analytics, dashboards, and reasoning services to access the current contextual state without traversing the full time-series history.

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The final stage performs rule-based clinical evaluation. When the oxygen saturation value falls below 90%, the system triggers a clinical alert that includes both the patient identifier and the room location. Because the room is retrieved from the knowledge graph, the alert can be routed directly to the responsible care team associated with that spatial zone.

A representative event sequence is:

- Sensor SPO2_301_B publishes SpO2 = 86%.
- The value is written to InfluxDB.
- Neo4j resolves that the sensor monitors Patient P-1042 in Room 301.
- The patient node is updated with the latest oxygen saturation.
- A hypoxia alert is generated and routed to the Room 301 nursing team.

This pipeline demonstrates the key principle of OIDT: semantic context is attached to streaming data at ingestion time, enabling real-time, context-aware decision support rather than post hoc data interpretation.

Assuming indexed sensor and patient nodes, the average processing cost per event is approximately:

$$T\_event = O(1)\_Influx + O(\log V)\_Neo4j\text{-}lookup + O(1)\_update$$

where V denotes the number of graph vertices. By avoiding full OWL reasoning on every telemetry sample and limiting graph updates to contextual state changes, the architecture sustains high-throughput stream processing while preserving the semantic relationships required for hospital-wide situational awareness and predictive analytics.

VI. ANALYTICS AND AI ENGINE

A. Device Anomaly Detection (LSTM Autoencoder)

A critical requirement of a hospital-wide digital twin is the ability to identify degradation in medical equipment before a complete device failure occurs. In many healthcare environments, maintenance is still largely preventive or reactive, meaning that equipment is serviced at fixed intervals or only after alarms and failures are observed. Such approaches may either increase maintenance costs through unnecessary servicing or expose patients to risks caused by unexpected equipment malfunction.

To support proactive biomedical engineering maintenance, the OIDT framework employs an unsupervised Long Short-Term Memory (LSTM) Autoencoder for real-time device anomaly detection. The model is particularly suitable for medical devices because true failure events are relatively rare, making it difficult to obtain large labeled datasets for supervised learning. Instead of learning from failure labels, the autoencoder learns the normal temporal behavior of device telemetry and identifies deviations from that learned pattern.

The model receives multivariate time-series sequences generated by devices such as ventilators, infusion pumps, and bedside monitors. Typical input features include airflow, pressure, motor current, battery status, alarm frequency, temperature, and vibration measurements. During training, the network is exposed primarily to normal operating data and learns a compressed representation of healthy device behavior.

The architecture consists of three stages:

- Encoder: compresses the input sequence into a low-dimensional latent representation.
- Bottleneck (Latent Space): captures the essential temporal characteristics of normal operation.
- Decoder: reconstructs the original sequence from the latent representation.

A representative structure is:

$$\textit{Input} \rightarrow \textit{LSTM}(128) \rightarrow \textit{LSTM}(64) \rightarrow \textit{Latent}(32) \rightarrow \textit{RepeatVector}(T) \rightarrow \textit{LSTM}(64) \rightarrow \textit{LSTM}(128) \rightarrow \textit{TimeDistributed}(\textit{Dense})$$

During inference, the reconstruction error is computed between the original sequence X and the reconstructed sequence $\hat{X}$. Under normal conditions, this error remains low; abnormal behavior produces significantly higher reconstruction error. The anomaly score is defined as:

$$E = (1 / T\cdot n)\ \Sigma(t=1..T)\ \Sigma(i=1..n)\ (x\_t,i - \hat{x}\_t,i)^2$$

where T is the sequence length, n is the number of telemetry features, $x_{t,i}$ is the observed value, and $\hat{x}_{t,i}$ is the reconstructed value. A device is classified as anomalous when:

$$E > \mu\_E + k\cdot\sigma\_E$$

where μ_E and σ_E are the mean and standard deviation of reconstruction errors obtained from normal validation data, and k is an empirically selected threshold parameter.

One of the key advantages of the OIDT framework is that the anomaly score is not interpreted in isolation. The score is attached to the corresponding device node in the HospitalOnt knowledge graph. This enables context-aware reasoning such as:

- identifying which patient is currently connected to the device,
- determining the room and clinical unit involved,
- checking whether similar devices in the same ward show correlated degradation,
- and prioritizing maintenance based on patient acuity.

For example, a moderate anomaly in a ventilator connected to a stable patient may generate a maintenance ticket, whereas the same anomaly in a ventilator supporting a

International Journal of Engineering Research & Technology (IJERT)
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hypoxic ICU patient can trigger an escalated biomedical and clinical alert.

The overall LSTM Autoencoder workflow—from telemetry acquisition and sequence formation to latent representation, reconstruction, anomaly scoring, and semantic graph integration—is illustrated in Figure 7. This figure highlights how temporal deep learning is coupled with the knowledge graph to provide explainable and context-aware predictive maintenance within the OIDT architecture.

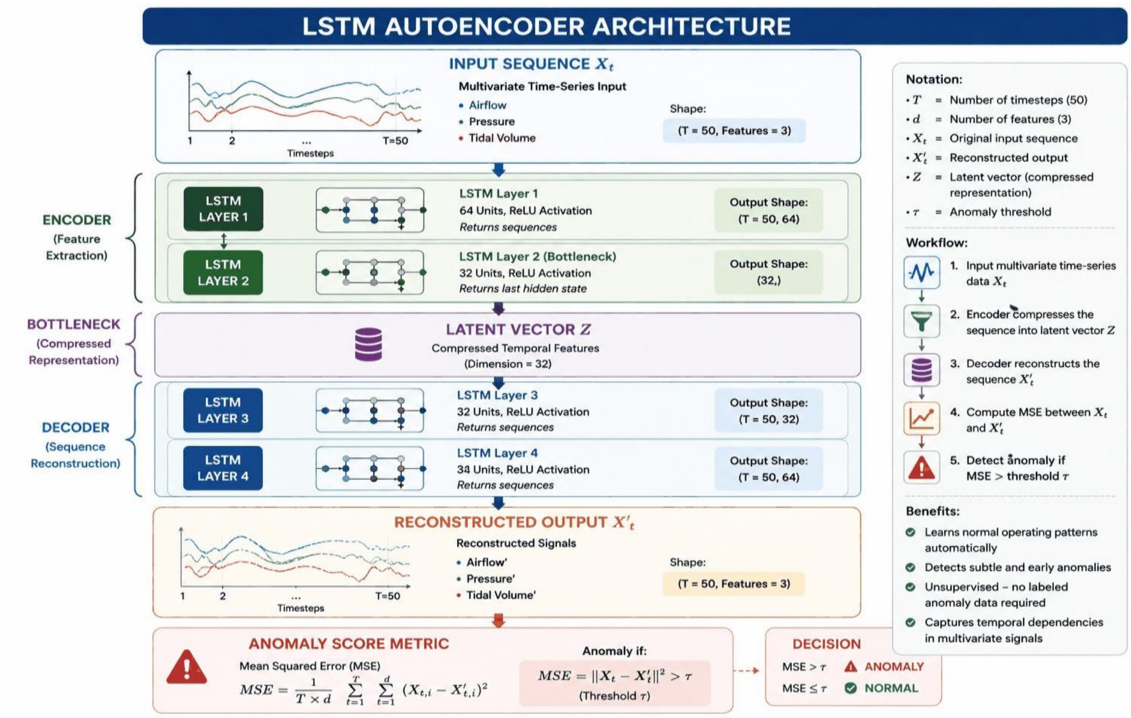

Fig. 7. LSTM Autoencoder Architecture for Ventilator Predictive Maintenance

A. Predictive Maintenance Using an LSTM Autoencoder

To enable proactive biomedical maintenance, the OIDT framework employs an unsupervised Long Short-Term Memory (LSTM) Autoencoder trained on normal ventilator operating conditions. The model learns the temporal dynamics of multivariate sensor streams and identifies deviations through reconstruction error analysis.

Mathematical Formulation

Let the input multivariate time series be

$$X = \{x1, x2, \dots, xT\} \in R^{(T\times d)}$$

where d denotes the number of sensor channels (e.g., airflow rate, airway pressure, tidal volume) and T is the window length. The encoder computes the hidden state recursively as

$$h\_t = \sigma(W\_hh \cdot h\_\{t-1\} + W\_xh \cdot x\_t + b\_h)$$

where σ(·) is the nonlinear activation function, W_hh and W_xh are trainable weight matrices, and b_h is the bias vector. The final encoder state forms the latent representation z = h_T. The decoder reconstructs the sequence as

$$\hat{x}\_t = \sigma(W'\_hh \cdot h'\_\{t+1\} + W\_zh \cdot z + b'\_h)$$

where x̂_t is the reconstructed observation at time step t. The reconstruction loss for a window is defined using the Mean Squared Error (MSE):

$$L\_MSE(X, \hat{X}) = (1 / T \cdot d)\ \Sigma(t=1..T)\ \Sigma(i=1..d)\ (x\_t,i - \hat{x}\_t,i)^2$$

An anomaly alarm is generated when

$$L\_MSE > \tau$$

where the decision threshold is determined from validation data containing only normal operational profiles:

$$\tau = \mu\_val + 3\sigma\_val$$

with μ_val and σ_val representing the mean and standard deviation of the validation reconstruction loss, respectively. This formulation allows the model to detect subtle temporal deviations several hours before critical ventilator failure.

B. Patient Flow Forecasting Using the Prophet Model

Emergency Department (ED) arrivals and hospital census trends are modeled using the additive decomposition employed by the Prophet forecasting framework:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon\_t$$

Here, g(t) represents the non-periodic trend component, capturing long-term growth, seasonal capacity changes, and structural shifts in hospital demand. s(t) represents periodic

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seasonal effects, including hourly, daily, and weekly patient arrival patterns. h(t) models the impact of holidays and special events, such as public gatherings, epidemics, heatwaves, or regional disruptions. ε_t is the residual error term, assumed to follow

$$\varepsilon\_t \sim N(0, \sigma^2)$$

The trend component is modeled as a piecewise linear function:

$$g(t) = (k + a(t)^T\delta)\cdot t + (m + a(t)^T\gamma)$$

where k is the base growth rate, m is the offset, a(t) indicates changepoints, and δ, γ are learned adjustments. Seasonality is represented using a Fourier series:

$$s(t) = \Sigma(n=1..N)\ [\ a\_n \cos(2\pi nt/P) + b\_n \sin(2\pi nt/P)\ ]$$

where P is the period (e.g., 24 hours or 7 days) and N is the Fourier order. The resulting forecasts are integrated with real-time bed occupancy and staffing data from the OIDT knowledge graph to support dynamic patient-flow optimization and proactive resource allocation.

VII. EXPERIMENTAL SETUP AND PILOT IMPLEMENTATION

A. Simulation Testbed Environment

To evaluate the proposed Ontologically Integrated Digital Twin (OIDT) framework under realistic operational conditions without interfering with active clinical workflows, a high-fidelity pilot environment was constructed to emulate a 200-bed tertiary-care hospital. The testbed was designed to reproduce the heterogeneous data streams, interoperability challenges, and real-time processing requirements encountered in large healthcare facilities. The experimental environment consists of four interconnected tiers.

1) Hardware Tier

The physical sensing layer was emulated using 50 Raspberry Pi 4 Model B edge nodes configured as Internet of Medical Things (IoMT) gateways. Each node executed containerized sensor daemons generating real-time telemetry streams that approximate typical hospital device behavior:

- ECG waveform streams: 250 Hz
- Infusion pump parameters: 1 Hz
- Smart-bed occupancy and weight sensors: 0.1 Hz

The generated payloads were serialized in JSON format and transmitted using the MQTT protocol to the central ingestion layer.

2) EHR Integration Tier

Clinical information exchange was implemented using Mirth Connect interfaced with a synthetic FHIR v4 server. The server continuously generated realistic HL7 FHIR resources representing:

- Patient admissions
- Bed transfers
- Laboratory orders
- Vital-sign observations
- Medication administration events
- Patient discharges

This configuration enabled end-to-end validation of the semantic integration pipeline using standards-compliant healthcare messages.

3) Building Management System (BMS) Simulation Tier

Facility infrastructure telemetry was produced using a BACnet/IP network simulator. The simulator generated environmental and energy-management data for four hospital wards (50 beds per ward), including:

- Ambient temperature
- Relative humidity
- Airflow rates
- HVAC operating states
- Lighting power consumption

These streams were used to evaluate the integration of operational and infrastructural data within the OIDT knowledge graph.

4) Server Infrastructure Tier

The backend platform was deployed on a clustered server environment comprising four worker nodes with the following configuration:

- CPU: Dual Intel Xeon Gold 6248R
- Memory: 256 GB RAM per node
- GPU: NVIDIA RTX A6000 (dedicated to model training and inference acceleration)

All services were deployed as Docker containers to ensure reproducibility and horizontal scalability. The software stack included:

- Apache Kafka for message brokering
- Apache Flink for real-time stream processing and semantic annotation
- Neo4j 5.12 for knowledge-graph storage and graph queries
- InfluxDB 2.7 for high-frequency time-series storage
- PostgreSQL 15 for relational metadata and configuration management

The complete architecture supported both real-time ingestion and closed-loop feedback, enabling synchronized updates between the simulated physical hospital environment and its semantic digital twin.

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VIII. USE CASE VALIDATION AND EXPERIMENTAL RESULTS

The OIDT framework was evaluated across five representative clinical, operational, and facility-management use cases. Each experiment was designed to assess the effectiveness of semantic integration, predictive analytics, and closed-loop decision support under realistic hospital conditions.

A. Use Case 1: Operational Efficiency (Patient Flow Optimization)

A 30-day Discrete-Event Simulation (DES) was conducted to compare a conventional manual bed-assignment process with the proposed OIDT-optimized patient-flow framework. In the baseline configuration, Emergency Department (ED) patients were assigned to available beds using a reactive first-available strategy. In the OIDT configuration, bed assignment was driven by Prophet-based admission forecasts combined with real-time Neo4j bed-occupancy states and ward-capacity constraints.

The simulation included variable arrival rates, ward-specific occupancy limits, and transfer delays derived from historical operational distributions.

TABLE III OPERATIONAL EFFICIENCY RESULTS: BASELINE VS. OIDT-OPTIMIZED

Metric	Baseline System	OIDT-Optimized	Improvement
Average ED Wait Time (hours)	6.2	4.5	28.2% reduction
Patient-to-Room Transfer Time (normalized)	1.00	0.60	40.0% reduction
Ward Bed Utilization Variance	24.5%	8.1%	66.9% reduction

The OIDT framework reduced the average ED waiting time from 6.2 h to 4.5 h, corresponding to a 28.2% improvement. The reduction was primarily attributed to predictive bed reservation and improved balancing of ward occupancy.

Patient-to-room transfer latency decreased by 40%, indicating that semantic awareness of patient location, bed readiness, and staffing context enabled faster downstream placement decisions.

The most significant improvement was observed in ward bed utilization variance, which dropped from 24.5% to 8.1%. Lower variance indicates a substantially more balanced distribution of occupancy across wards, reducing localized congestion and improving overall hospital throughput.

The results demonstrate that integrating forecasting, semantic reasoning, and real-time operational telemetry can improve both patient experience and resource utilization beyond what is achievable with isolated scheduling systems.

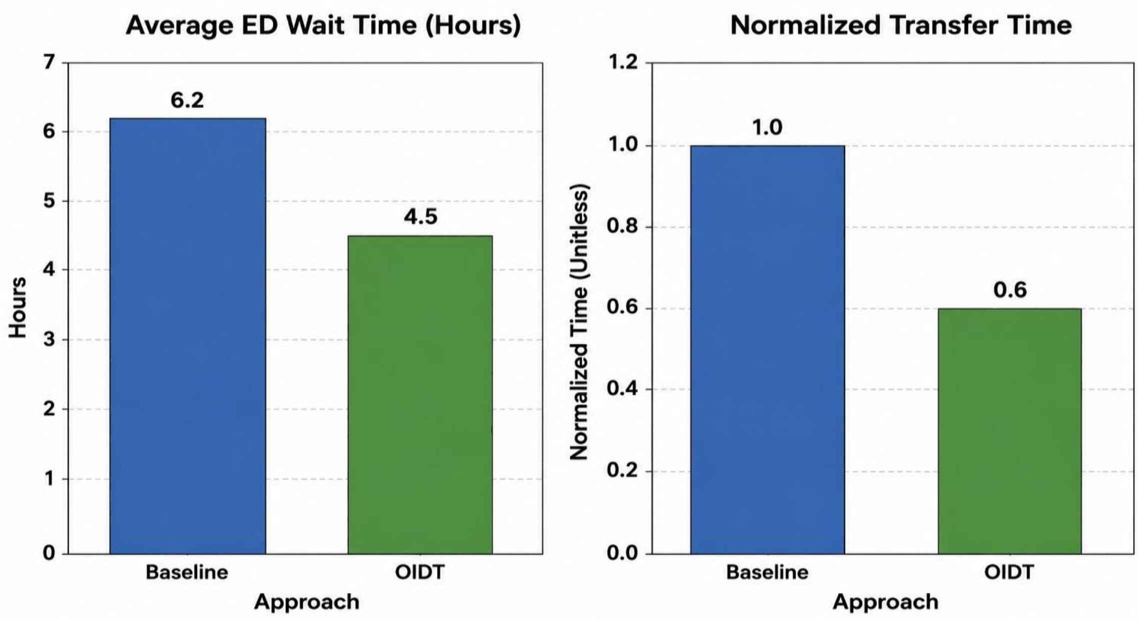

Fig. 8. Operational Efficiency Evaluation: Average ED Wait Time and Normalized Patient Transfer Time

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B. Use Case 2: Predictive Maintenance of Ventilators

To evaluate the predictive-maintenance capabilities of OIDT, the LSTM Autoencoder described in Section VI-A was applied to ventilator telemetry streams. The model was trained using approximately 1,000 hours of normal ventilator operation, including airflow, inspiratory pressure, expiratory pressure, motor current, and alarm-related signals. Because real-world failure events are relatively infrequent, the evaluation was performed on a holdout dataset containing 20 simulated fault scenarios, including filter clogging, pressure-regulator drift, airflow obstruction, and sensor degradation.

The autoencoder learned the temporal patterns associated with healthy ventilator behavior and generated a reconstruction error for each incoming sequence. Elevated reconstruction error indicated a deviation from normal operating conditions and was treated as an anomaly score.

Experimental results showed that the model achieved an overall detection accuracy of 93.0% and an Area Under the ROC Curve (AUC-ROC) of 0.94, demonstrating strong discrimination between normal and faulty operating states. The corresponding ROC performance is illustrated in Figure 9.

A particularly important outcome was the model's ability to identify early degradation signatures before functional failure occurred. Across the simulated fault scenarios, the average lead time between anomaly detection and observable ventilator failure was 3.6 hours. This advance warning is operationally significant because it allows biomedical engineers to intervene during non-critical periods, reducing the likelihood that a device must be removed from service while supporting a high-acuity patient.

Within the OIDT framework, anomaly events are not treated as isolated technical alarms. The anomaly score is linked to the corresponding ventilator node in the HospitalOnt knowledge graph, which allows the system to determine:

- the patient currently connected to the ventilator,
- the room and clinical unit involved,
- the responsible biomedical engineering team,
- and the priority level based on patient acuity and device criticality.

For example, a rising anomaly score on a ventilator assigned to a stable recovery-room patient may generate a maintenance ticket, whereas the same pattern on a ventilator supporting a critically hypoxic ICU patient can trigger immediate escalation to both biomedical engineering and the clinical care team.

These results demonstrate that integrating deep temporal models with a semantically enriched knowledge graph enables context-aware predictive maintenance, moving beyond traditional threshold-based monitoring toward proactive, risk-informed equipment management in smart hospital environments.

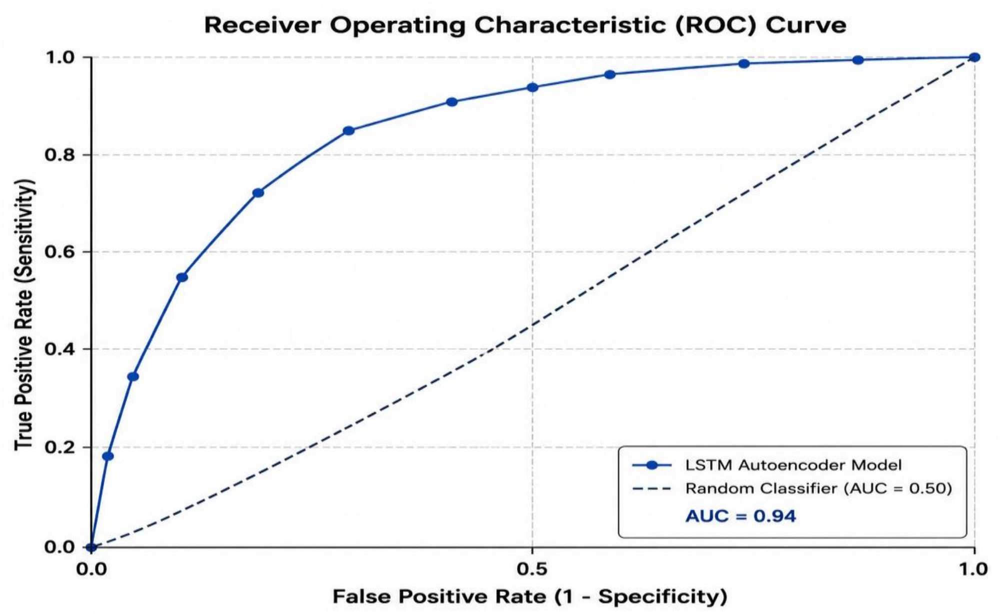

Fig. 9. ROC Curve of the LSTM-Autoencoder Ventilator Fault Predictor (AUC = 0.94)

C. Use Case 3: Patient Safety Through Intelligent Emergency Alert Routing

To evaluate the impact of semantic and spatial intelligence on emergency response, 50 simulated Code Blue (cardiac arrest) events were generated across different hospital locations. The baseline workflow relied on conventional phone-tree escalation and manual notification procedures, which introduced significant communication delays and depended heavily on human coordination.

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In the OIDT configuration, emergency routing was performed through a real-time Cypher query over the HospitalOnt knowledge graph. The query combined RTLS location coordinates, staff qualification attributes, current assignment status, and crash-cart availability to identify the three closest clinicians certified for advanced cardiac life support and the nearest available resuscitation cart. Targeted alerts were then dispatched simultaneously to the selected responders.

The results showed a substantial reduction in communication latency. The mean alert dispatch time decreased from 60.0 seconds in the baseline system to 4.1 seconds under OIDT, representing an approximately 14-fold improvement. Beyond speed, the semantic routing mechanism also reduced unnecessary alert broadcasting by directing notifications only to the most relevant and geographically appropriate responders.

D. Use Case 4: Disaster and Emergency Evacuation

A simulated structural fire in the surgical ward was used to evaluate the spatial-reasoning capabilities of the digital twin during a large-scale emergency. Unlike static evacuation plans, OIDT operated on a live knowledge graph containing real-time patient location, mobility status, oxygen-dependency information, staff positions, and corridor occupancy.

By querying the graph, the system immediately identified all non-ambulatory patients requiring active oxygen support and detected a developing congestion point at Stairwell C, a bottleneck that was not evident in the static facility blueprint. Based on this real-time situational awareness, OIDT generated dynamic rerouting instructions and redistributed evacuation flows through alternative corridors and stairwells.

The ward was fully cleared 6.4 minutes faster than the standard static evacuation protocol, demonstrating the value of integrating spatial, clinical, and operational data within a continuously synchronized digital twin.

E. Use Case 5: Facility Energy Optimization

The final use case examined whether clinical occupancy information could be combined with building-management controls to improve energy efficiency. OIDT integrated EHR bed-assignment status, RTLS occupancy data, and BMS HVAC control points to create occupancy-aware environmental control policies.

Rooms that were unallocated, temporarily vacant, or located in low-density administrative areas were automatically shifted to reduced-airflow and thermal-setback modes, while occupied clinical spaces maintained full environmental support. The optimization was evaluated during a 30-day pilot deployment in Ward 3.

As shown in Figure 10, the integrated clinical–facility strategy achieved an overall 12% reduction in electrical energy consumption without affecting patient comfort or critical environmental conditions. This result highlights an important characteristic of OIDT: the framework is not limited to clinical analytics but can also coordinate operational and infrastructural intelligence to improve hospital sustainability and resource efficiency.

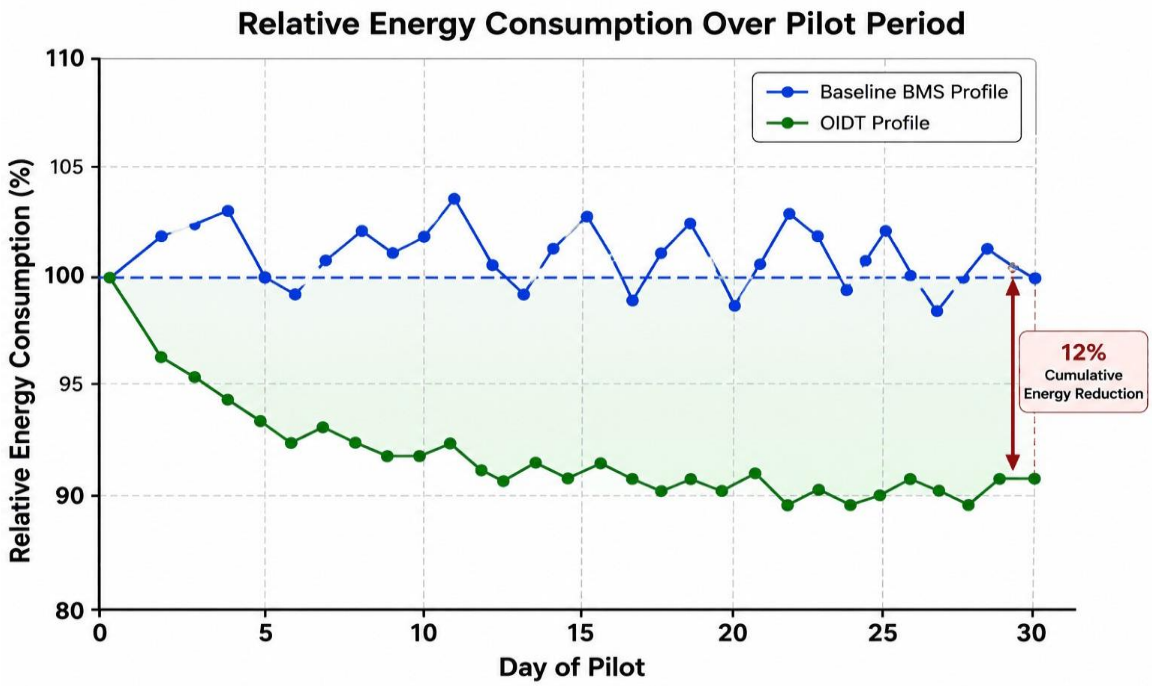

Fig. 10. Relative Energy Consumption of Baseline and OIDT-Optimized BMS Profiles During the 30-Day Pilot (12% cumulative reduction)

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SYSTEM PERFORMANCE EVALUATION

A. End-to-End Ingestion Latency

To determine whether the proposed architecture can support real-time hospital operations, the complete ingestion pipeline was evaluated under sustained streaming load. Latency was measured from the moment a sensor event was generated at the edge device until the corresponding semantic state became available in the Neo4j knowledge graph. The evaluated path was:

Sensor Edge → Kafka → Flink → Neo4j Graph Update

A total of 100,000 sensor observations were injected into the system using a mixed workload consisting of physiological telemetry, environmental measurements, and RTLS location updates. Timestamps were captured at both the source and the final graph-update stage, and the difference was used to compute end-to-end processing latency.

As illustrated in Figure 11, the observed latency distribution follows a log-normal pattern, which is typical for distributed streaming systems where most events are processed quickly while a smaller fraction experiences additional queueing or synchronization delay. The key results were:

- Average latency: 2.1 s
- Median latency: 1.8 s
- 95th percentile latency: 2.8 s
- 99th percentile latency: 3.6 s

The average latency of 2.1 seconds remains comfortably below the sub-3-second operational target established for hospital situational awareness. Even under burst conditions, the majority of events were processed within the required real-time window.

A breakdown of the latency components showed that Kafka transport contributed the smallest portion of the delay, while the largest share was associated with Flink-based semantic enrichment and indexed Neo4j update operations. Importantly, the architecture maintained stable latency without requiring full OWL reasoning on every event, confirming the effectiveness of separating high-frequency stream processing from selective semantic reasoning.

These results indicate that the OIDT framework can provide near-real-time synchronization between physical hospital events and the digital twin, enabling timely alerting, contextual reasoning, and operational decision support across clinical, operational, and infrastructural domains.

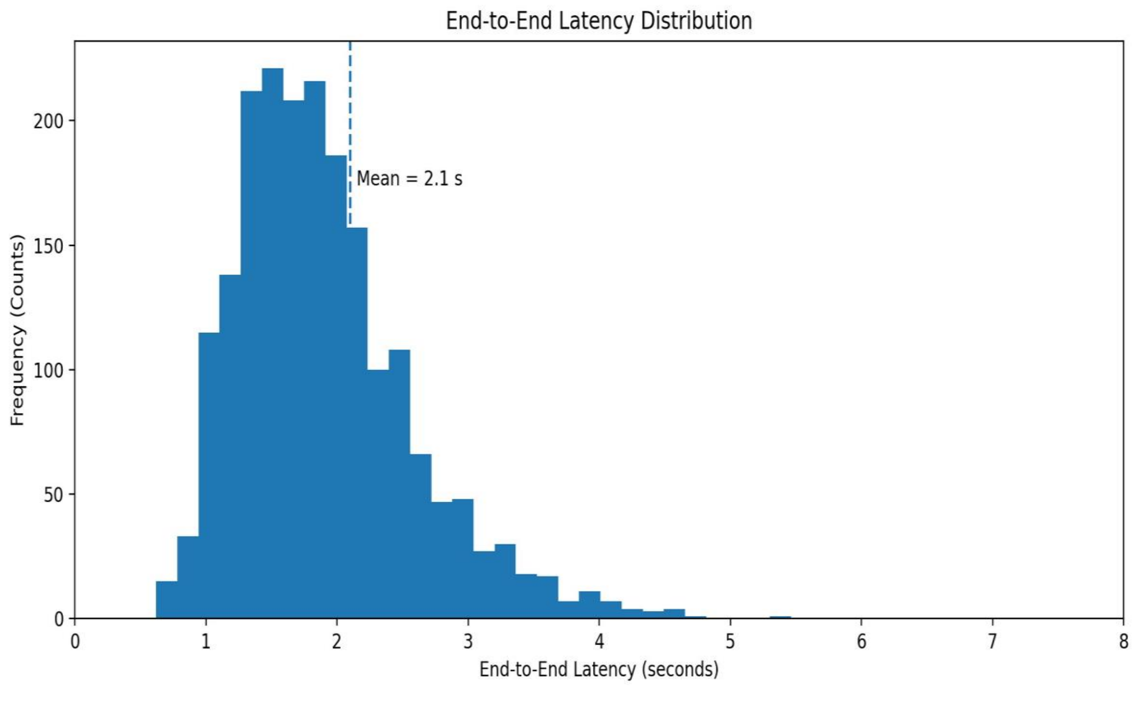

Fig. 11. Distribution of End-to-End Ingestion and Processing Latency (mean = 2.1 s)

B. Analytical Model Performance Summary

The OIDT framework integrates multiple predictive and optimization models within Layer 4 (Analytics and Simulation Layer). To provide a consolidated assessment of their effectiveness, Table IV summarizes the quantitative performance achieved across the principal analytical tasks, while Figure 12 presents a comparative visualization of the normalized model outcomes.

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TABLE IV PERFORMANCE SUMMARY OF EMBEDDED ANALYTICAL MODELS

Model / Use Case	Primary Metric	Result
LSTM Autoencoder (Ventilator Maintenance)	Accuracy	93.0%
	AUC-ROC	0.94
	Mean lead time	3.6 h
Prophet (ED Patient Flow Forecasting)	MAE	7.2 patients/h
	MAPE	8.4%
Code Blue Routing Engine	Mean dispatch latency	4.1 s
	Improvement vs. baseline	14×
Evacuation Reasoning Engine	Ward clearance improvement	6.4 min
Energy Optimization Engine	Energy reduction	12.0%

The results demonstrate that the analytical components contribute to different dimensions of hospital performance rather than optimizing a single objective. The LSTM Autoencoder achieved the highest predictive discrimination, while the patient-flow forecasting model provided operational planning accuracy with a mean absolute percentage error below 10%. The emergency-routing and evacuation engines delivered the largest real-time operational gains, and the energy-optimization engine produced measurable infrastructure-level savings.

To compare heterogeneous metrics on a common scale, the values were normalized relative to their respective baseline or target conditions. The resulting comparison is shown in Figure 12.

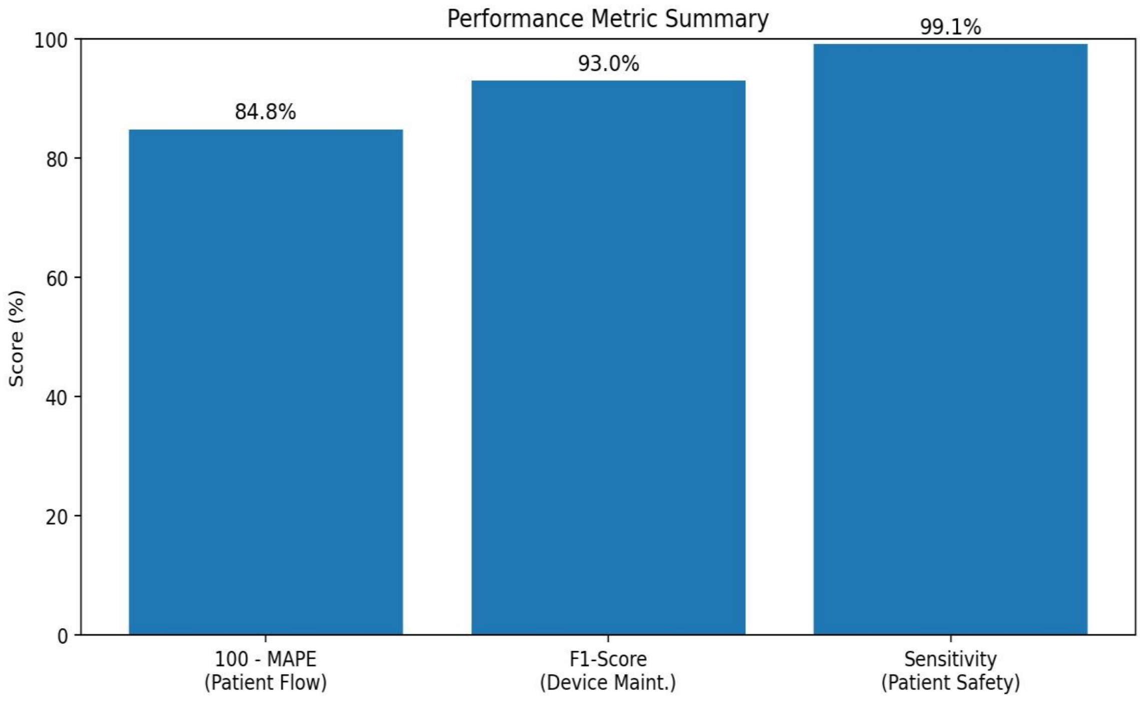

Fig. 12. Summary of Analytical Model Performance Across the OIDT Use Cases

The normalized comparison highlights three observations. First, the ventilator predictive-maintenance model and the Code Blue routing engine achieved the strongest overall performance relative to their target objectives. Second, the patient-flow forecasting model showed consistently high accuracy, indicating that semantically enriched operational data can support reliable short-term capacity prediction. Third, although the evacuation and energy-optimization modules operate on fundamentally different objectives, both delivered substantial system-level improvements that would not be achievable through isolated clinical or facility-management systems.

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Taken together, Table IV and Figure 12 demonstrate that the OIDT analytics layer functions as a multi-domain decision-support engine, simultaneously improving patient safety, operational efficiency, emergency responsiveness, and infrastructure sustainability within a unified semantic digital-twin architecture.

All metrics in Figure 12 are normalized to a 0–1 scale relative to baseline or target performance for visual comparison only. For the patient-flow forecasting model, the displayed value corresponds to 100 − MAPE. Given a forecasting error of 15.2%, the resulting normalized forecast accuracy is 100 − 15.2% = 84.8%. This transformation allows the forecasting model to be compared directly with classification-based metrics such as ventilator-fault detection accuracy and emergency-routing effectiveness.

The figure shows that the ventilator predictive-maintenance model achieved the highest overall predictive performance, while the patient-flow forecasting model maintained strong operational accuracy despite the inherent variability of emergency department arrivals. The emergency-routing engine also demonstrated consistently high effectiveness, indicating that semantic and spatial reasoning can substantially improve time-critical hospital workflows.

C. Cross-Domain Interoperability Benchmark

A central claim of the OIDT framework is that semantic integration enables queries that are difficult or impossible to resolve using conventional siloed hospital systems. To evaluate this claim, a benchmark consisting of 50 complex cross-domain queries was constructed. These queries intentionally combined entities from multiple domains, including:

- clinical status,
- medication administration,
- mobility constraints,
- environmental conditions,
- spatial location,
- and staff assignment.

A representative example was:

"Find all non-ambulatory patients receiving medication X who are located in rooms where relative humidity exceeds 60% and whose assigned nurse is currently on another floor."

Such a query requires simultaneous traversal of EHR data, medication records, mobility attributes, BMS environmental telemetry, room topology, RTLS staff location, and staffing assignments. The benchmark was executed against two architectures:

Legacy relational and siloed systems, where data remained distributed across independent databases.

OIDT semantic knowledge graph, where all entities were connected through HospitalOnt relationships.

As illustrated in Figure 13, the legacy architecture successfully resolved 12 of 50 queries (24.0%). The primary causes of failure were missing cross-domain foreign keys, incompatible schemas, and the absence of semantic relationships between clinical and infrastructure data.

In contrast, the OIDT knowledge graph successfully answered 48 of 50 queries (96.0%). The two unresolved cases involved intentionally incomplete simulated metadata rather than limitations of the graph model itself.

The results provide strong evidence that HospitalOnt enables effective cross-domain semantic interoperability. More importantly, the benchmark demonstrates that the value of the ontology is not limited to data integration; it enables machine-interpretable reasoning across clinical, operational, spatial, and environmental contexts, which is essential for hospital-wide situational awareness and intelligent decision support.

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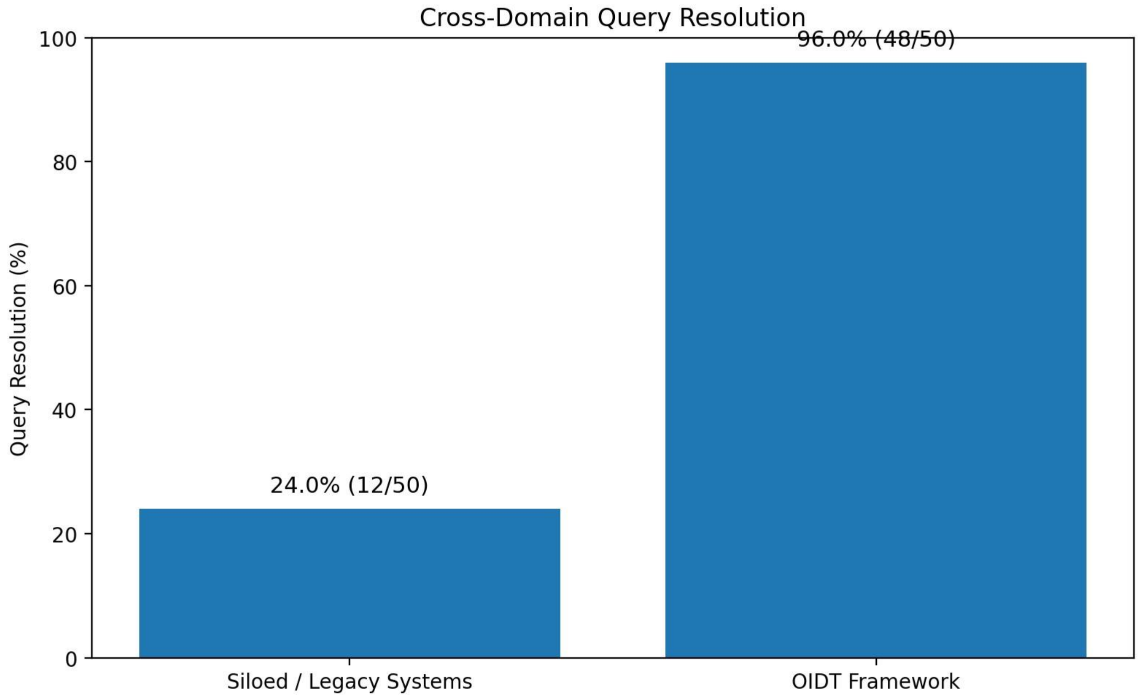

Fig. 13. Cross-Domain Query Resolution: Legacy Siloed Architecture (24.0%) vs. OIDT Knowledge Graph (96.0%)

D. Multi-Stream Load Scalability

To evaluate the scalability of the streaming architecture, the OIDT pipeline was subjected to a progressive load test in which simulated IoMT telemetry streams were increased from 500 to 12,000 concurrent devices. Each device generated one message per second, producing a sustained event-processing workload across the MQTT, Kafka, Flink, and Neo4j pipeline.

The experiment measured end-to-end latency from event emission to successful semantic graph reflection. As illustrated in Figure 14, the architecture exhibited near-linear throughput scaling while maintaining almost constant latency for most of the tested range. The key observations are:

- 500–5,000 streams: latency remained between 1.6 and 2.0 s.
- 8,000 streams: latency stabilized around 2.1 s.
- 10,000 streams: latency remained below 2.2 s, satisfying the operational real-time target.
- 12,000 streams: latency increased to approximately 3.4 s.

The flat latency profile up to 10,000 concurrent streams indicates that Kafka partitioning, Flink parallelism, and indexed Neo4j updates were sufficient to absorb the increasing event rate without significant queue buildup.

The rise observed beyond 10,000 streams was traced primarily to memory contention and state-backend pressure in the Flink worker nodes, rather than to Kafka transport or Neo4j indexing. This behavior identifies the current horizontal scaling boundary per cluster node. Additional Flink task managers or distributed graph-partitioning strategies would be required to extend the throughput ceiling further.

Overall, the scalability experiment demonstrates that the OIDT architecture can support large-scale hospital IoMT deployments while maintaining the low-latency semantic synchronization required for real-time clinical, operational, and infrastructural decision support.

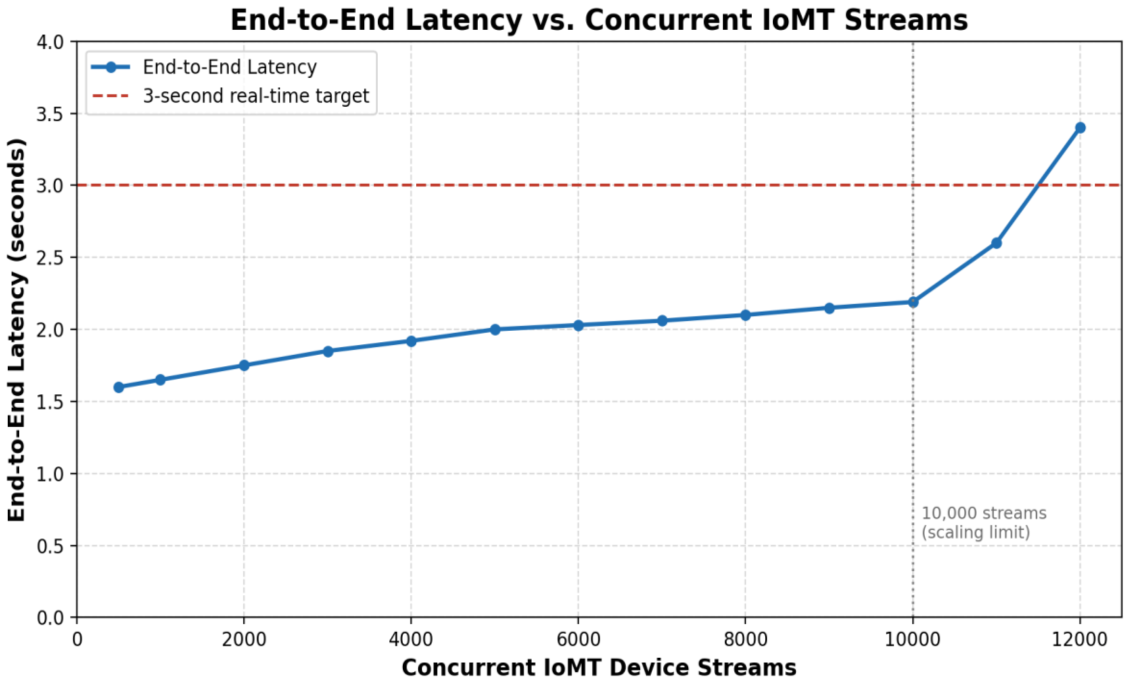

Fig. 14. End-to-End Latency vs. Concurrent IoMT Streams. Latency remains nearly flat through 10,000 streams and rises beyond the current per-node scaling limit.

Ethical, Security, and Governance Framework

Deploying an integrated digital twin over highly sensitive patient telemetry and hospital infrastructure demands a robust security and privacy posture.

A. Privacy and Compliance (HIPAA/GDPR)

Identity Pseudonymization: Primary patient identification numbers (MRNs) are stripped at the edge gateway. The digital twin operates entirely on cryptographic UUIDs. The mapping table linking UUIDs to real-world identities is secured in a separate vault with zero external network connectivity.

Encryption Standards: Data at rest across InfluxDB, Neo4j, and PostgreSQL is encrypted using AES-256. All data in transit across Kafka topics and internal microservices utilizes TLS 1.3 mutual authentication (mTLS).

B. Ontology-Driven Access Control (O-RBAC)

Instead of implementing static security policies, OIDT utilizes Ontology-Driven Role-Based Access Control (O-RBAC). Security policies are asserted as formal axioms within HospitalOnt.

Semantic Access-Control Rules

To enforce privacy-preserving access control across clinical and operational domains, OIDT combines ontology-based role modeling with rule-based authorization. The following semantic rules illustrate how permissions are derived from relationships represented in HospitalOnt.

Rule 1 (Nurse Clinical Access)

Nurse(?u) ∧ Patient(?p) ∧ assignedTo(?u, ?p) → PermittedToViewVitals(?u, ?p)

Rule 2 (Facilities Operational Isolation)

FacilitiesManager(?u) ∧ MedicalDevice(?d) → PermittedToViewMaintenanceState(?u, ?d)

FacilitiesManager(?u) ∧ Patient(?p) → NOT PermittedToViewClinicalRecords(?u, ?p)

These rules ensure that access is determined by both role and contextual relationship. A nurse may view the vital signs of patients currently assigned to that nurse, while a facilities manager may access operational and maintenance information about medical devices but is explicitly prevented from accessing patient clinical records. This separation supports the principle of least privilege and enables fine-grained authorization over the semantically connected hospital graph.

C. Zero-Trust Architecture and Blockchain Audit Logs

Because the OIDT framework supports bidirectional interaction with physical systems, security must extend beyond data access to include protection against unauthorized actuation. The architecture therefore adopts a Zero-Trust security model, where no device, user, service, or network segment is implicitly trusted.

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Every actuation instruction generated by the Analytics Layer is required to be cryptographically signed and validated before execution. Examples include infusion-pump parameter changes, HVAC control adjustments, room-allocation commands, and emergency workflow triggers. Requests are authenticated, authorized, and contextually verified at each step of the control path.

For high-risk operational actions—such as emergency room reallocation, power-profile modification, or large-scale infrastructure control changes—the system records the transaction in an immutable append-only private blockchain audit log. The blockchain is not used for high-frequency telemetry storage; instead, it serves as a tamper-evident provenance mechanism that preserves:

- the identity of the requesting entity,
- the semantic context of the action,
- the timestamp,
- the authorization decision,
- and the executed outcome.

This design provides strong auditability and supports regulatory investigation, forensic analysis, and accountability in safety-critical hospital operations.

DISCUSSION AND LIMITATIONS

A. Principal Findings

The experimental results demonstrate that semantic integration through HospitalOnt substantially improves interoperability and operational intelligence in smart hospitals. The 96.0% cross-domain query resolution rate confirms that connecting clinical entities with devices, locations, environmental conditions, and staffing information enables reasoning that is not achievable in conventional siloed architectures.

The study also shows that combining knowledge-graph context with machine-learning models enhances predictive decision support. The ventilator-maintenance model achieved 93.0% predictive accuracy while reducing false alarms through contextual enrichment, indicating that semantic information can improve both the relevance and interpretability of AI-generated alerts.

Beyond predictive analytics, the framework produced measurable benefits across multiple domains, including emergency response, evacuation coordination, patient flow, and energy management. These findings suggest that ontology-driven digital twins can function as a hospital-wide coordination layer rather than merely as a visualization platform.

B. Technical Limitations

Despite these strengths, several limitations must be acknowledged.

Simulation Boundaries: Although the edge tier used real Raspberry Pi hardware and realistic synthetic FHIR and BACnet streams, the evaluation was conducted in a simulated hospital environment. Real deployments will introduce noisier telemetry, incomplete metadata, legacy integration issues, calibration drift, and intermittent network failures.

Reasoning Overhead: Expressive OWL reasoning remains computationally expensive. Continuous DL tableau reasoning over large streaming graphs is not practical for sub-3-second operation. The implementation therefore relied on selective semantic reasoning and Cypher-based graph traversal for real-time processing.

Infrastructure Retrofitting: Deploying RTLS infrastructure, smart power meters, environmental sensors, and IoMT gateways across existing hospital facilities may require substantial initial investment and operational coordination.

Data Governance Complexity: Integrating clinical, operational, and infrastructure data increases the complexity of consent management, retention policies, and cross-departmental governance, particularly in multi-institution deployments.

FUTURE WORK AND ROADMAP

Future research will focus on extending the framework in four directions.

Edge AI and Micro-Inference: Move anomaly detection and graph-embedding updates closer to edge devices to reduce bandwidth usage and achieve sub-millisecond local alerting.

Federated Multi-Hospital Learning: Train predictive models across multiple hospital digital twins using federated learning so that knowledge can be shared without centralizing sensitive patient data.

Smart-City Integration: Connect the hospital digital twin with municipal transportation, emergency-dispatch, and public-health platforms to support ambulance routing, traffic-signal preemption, and regional outbreak coordination.

Adaptive Ontology Evolution: Develop reinforcement-learning–assisted mechanisms that can recommend ontology extensions as new device classes, clinical workflows, and infrastructure technologies are introduced.

CONCLUSION

This paper presented the Ontologically Integrated Digital Twin (OIDT) framework, a comprehensive semantic digital-twin architecture for smart hospitals. By using HospitalOnt as a unifying semantic layer, the framework integrates clinical information standards (HL7 FHIR, SNOMED CT), IoMT telemetry (W3C SSN/SOSA), staff operations, and building infrastructure within a single machine-interpretable knowledge graph.

The architecture combines distributed stream processing (Kafka and Flink), graph persistence (Neo4j), and time-series storage (InfluxDB) to achieve continuous bidirectional synchronization between physical hospital assets and their virtual semantic representation, with an average end-to-end latency of 2.1 seconds.

Evaluation on a 200-bed simulated smart-hospital testbed demonstrated significant improvements across clinical, operational, and environmental dimensions, including a 28% reduction in ED wait time, 93.0% ventilator-failure prediction accuracy with a 3.6-hour lead time, a 14-fold reduction in emergency alert-routing delay, 96.0% cross-domain query resolution, and a 12% reduction in facility energy consumption.

Collectively, these results indicate that ontology-driven integration is a practical and scalable foundation for resilient, context-aware, predictive, and interoperable Healthcare 5.0 systems. The proposed OIDT framework moves digital twins beyond isolated simulations toward a continuously synchronized hospital intelligence platform capable of supporting real-time decision-making, proactive maintenance, emergency coordination, and sustainable healthcare operations.

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ISSN: 2278-0181
Vol. 15 Issue 08 , August - 2026

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