Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Ampere: A Digital Twin-Enabled Cyber-Physical IoT Node for Environmental Health Monitoring in IoMT Systems

Sridatta Gorthi

sdkgorthi@protonmail.com

Kendriya Vidyalaya Sanghathan https://orcid.org/0009-0007-0560-5139

Research Article

Keywords: Internet of Things (IoT), Cyber-Physical Systems (CPS), Digital Twin, Environmental Health Monitoring

Posted Date: July 3rd, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10227456/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: The authors declare no competing interests.

Ampere: A Digital Twin-Enabled Cyber-Physical IoT Node for Environmental Health Monitoring in IoMT Systems

*Sridatta Karthikeya Gorthi

Kendriya Vidyalaya Sangathan, New Delhi, India.

sdkgorthi@protonmail.com

Abstract. The Internet of Medical Things (IoMT) has transformed clinical care through connected biosensors that continuously monitor patient vitals, yet the environmental conditions that fundamentally govern infection transmission, air quality degradation, and patient recovery remain outside its operational scope. In high-traffic healthcare and institutional settings, factors such as particulate contamination, volatile organic compound accumulation, and inadequate surface hygiene directly influence public health outcomes — but conventional infrastructure lacks the sensing, connectivity, and intelligence to detect or respond to these risks. This paper introduces the Internet of Environmental Medical Things (IoEMT), a framework that extends medical IoT from patient-worn devices to the built environment itself, enabling stationary infrastructure to sense, reason about, and autonomously respond to environmental health conditions in real time.

To operationalize this framework, the Ampere node is presented: a cyber-physical smart hygiene system whose four-layer architecture unifies multi-modal environmental sensing ($PM_{2.5}$, CO_2, VOC), adaptive airflow control, Far-UVC (222 nm) sterilization governed by occupancy-gated safety interlocks, smoothed and filtered sensor fusion for noise-robust state estimation, and MQTT-based telemetry within a single edge-intelligent device. A machine learning classification pipeline processes fused sensor streams to categorize ambient conditions into four hygiene triage levels — from nominal operation through to emergency alert — driving automated, context-aware facility responses without human intervention. A bidirectional Digital Twin architecture couples each deployed physical node to a continuously synchronized virtual replica, enabling remote facility monitoring, spatial anomaly visualization through interactive dashboards, and predictive maintenance across distributed institutional networks. A defense-in-depth security architecture addresses the unique threat surface of healthcare CPS nodes, where compromised actuators pose physical safety risks beyond conventional data breaches.

Keywords: Internet of Things (IoT) · Cyber-Physical Systems (CPS) · Digital Twin · Environmental Health Monitoring

1 Introduction

1.1 The Public Health Imperative for Smart Infrastructure

Global health infrastructure is currently undergoing a significant digital transformation [1]. The traditional model of healthcare, which is largely reactive and centered on clinical environments, is evolving toward a proactive, decentralized model of continuous monitoring and prevention. Within this new paradigm, the "built environment"—the physical spaces where humans congregate—serves as the primary stage for pathogen transmission and the management of environmental health risks, for which UV-C has emerged as a major contender for a solution [2]. High-traffic institutional facilities are increasingly recognized as "hotspots" where air quality and surface hygiene directly correlate with public health outcomes [3]. Unseen pollutants and toxic gases enter into the air, and often they go dangerously unnoticed. In many cases, the environmental conditions of patient rooms are not conducive to optimal recovery.

Despite these advancements, a significant portion of the built environment's infrastructure remains technologically stagnant. Hygiene appliances, specifically hand-drying systems, typically operate as simple electromechanical loads. They are often energy-intensive, prone to microbial buildup in moist internal ducts, and entirely disconnected from broader facility management or Hospital Information Management Systems (HIMS). The Internet of Medical Things (IoMT) is a pioneering concept which is shaping and improving the wellbeing of patients in hospitals – and as environmental determinants such as air quality, sanitation infrastructure, and hygiene systems play a critical role in public health [4], although the Internet of Medical Things (IoMT) has enabled connected clinical devices, it has significantly enhanced patient diagnosis through smart sensors monitoring metrics of patient health [5]. But integration of environmental health infrastructure into connected medical ecosystems remains limited [6]. To address this gap, this work introduces the concept of the Internet of Environmental Medical Things (IoEMT) which combines the concept of twins and focuses on the effects of the external environment relevant to the object of medical things. Ampere is an intelligent IoEMT node which operationalizes this framework. It bridges the gap by bringing forward an IoMT-IoRT powered unified, intelligent hand-drying system that combines precision airflow, UV-C sterilization, energy harvesting, air quality monitoring, and adaptive user interaction to enhance hygiene, sustainability, and facility intelligence. Its framework presents a way towards pathogen-aware modelled devices for reducing possible infections, and a smart hub of connecting smart infrastructure of the healthcare microgrid [7].

1.2 History of Hygiene Infrastructure and Hand-Drying Systems

The history of public hygiene infrastructure reflects a slow but steady progression from manual interventions to automated electromechanical systems. In the mid-20th century, the standard for public hand hygiene was limited to manual cloth or paper towel dis-

pensers. While effective at moisture removal, these systems introduced significant logistical burdens, including waste management and the potential for cross-contamination through physical contact with dispenser levers.

The introduction of the first electric hand dryers in the late 1940s marked the first "modern" change in hygiene infrastructure. These early units were "binary" in operation—controlled by a physical button and a fixed-duration timer. By the 1980s, the integration of passive infrared (PIR) sensors allowed for touchless operation, a critical milestone in reducing the spread of contact-based pathogens. However, even these automated units remained "black boxes" in terms of data. They operated in isolation, with no mechanism to report their operational health, energy consumption, or the environmental conditions of the restroom in which they were installed.

1.3 Modern Changes: The Transition to IoMT and Industry 4.0

The advent of Industry 4.0 and the Internet of Things (IoT) has provided the technological catalyst for the most significant modern change in hygiene infrastructure: the shift from "automated" to "intelligent" [8]. In the context of Connected Health, this involves the integration of low-cost, high-precision sensors and high-speed telemetry. Modern systems, especially Cyber-physical systems act as intelligent hubs combining computational power with manual efficiency, and hygiene systems, especially, are no longer restricted to simple on/off cycles [9]; they can now modulate airflow based on user proximity, track usage patterns to optimize maintenance schedules, and monitor ambient air quality to detect chemical or biological anomalies.

The transition toward the Internet of Medical Things (IoMT) further expands this paradigm of connected healthcare. Traditionally, IoMT has been associated with wearable biosensors and remote patient monitoring (RPM) devices that continuously track physiological parameters [10]. However, the scope of IoMT is gradually extending beyond patient-centric wearables to include environment-aware medical infrastructure [11].

In this direction, this paper introduces the Internet of Environmental Medical Things (IoEMT)— an integrated digital health framework that extends the capabilities of the Internet of Medical Things by incorporating environmental sensing, together integrating intelligent infrastructure, and artificial-intelligence–driven analytics to interpret both environmental conditions and patient-related health data. Through Physical Twin–Digital Twin coupling, and ensuring that systems to detect problems and intrusions are in place [20], IoEMT systems can analyze environmental and health-related data streams, simulate operational scenarios, keep public health data protected, and determine optimal operational cadences for specific public environments.

Unlike wearable devices that focus on individual patient metrics, IoEMT nodes observe environmental conditions that directly influence patient health and hospital safety. Studies have explored potential of smart patient monitoring, but in connection with this field remain limited, although other papers have explored particulate and air monitoring as a non-integrated approach [12,13].

For instance, a smart hygiene node capable of monitoring Particulate Matter ($PM_{2.5}$) and Volatile Organic Compounds (VOCs) in a hospital ward can provide continuous

environmental intelligence. Such data streams are critical because air quality, contamination levels, and chemical exposure can affect infection control and patient recovery. Consequently, environmental sensing systems may be considered just as vital to clinical safety as traditional physiological monitoring devices such as bedside heart-rate monitors.

The concept of IoEMT therefore represents a natural evolution of IoMT, integrating environmental sensing, intelligent analytics, and healthcare infrastructure monitoring to create safer and more responsive clinical spaces. To distinguish between the proposed IoEMT framework from existing paradigms, a comparative analysis is presented in Table 1.

Table 1. Comparative analysis of IoT, IoMT, CPS, smart building systems, and the proposed IoEMT framework

Feature	IoT	IoMT	CPS	Smart Buildings	IoEMT
Focus	Devices	Patients	Control	Infrastructure	Env + health
Data	General	Physiological	Sensor	Environmental	Multi-modal
Logic	Basic	Clinical	Feedback	Automated	AI + DT
DT use	Rare	Emerging	Common	Limited	Core
Scope	General	Healthcare	Industrial	Buildings	Healthcare-oriented env.

As shown in Table 1, the proposed IoEMT framework differs from existing paradigms by explicitly integrating environmental sensing with healthcare-oriented decision-making within a unified Digital Twin–enabled architecture. Unlike conventional IoMT systems that primarily focus on patient-centric physiological monitoring, IoEMT extends the scope to environment-driven health inference and infrastructure-level adaptation.

2 Related Work

Recent literature has highlighted the transformative potential of Digital Twins (DTs) in healthcare management [14]. A Digital Twin is a virtual representation of a physical artifact that depicts its real-world behavior in a virtual space [15]. These models utilize multiple interoperable data streams—including analytical, geometric, and behavioral models—to develop living simulations that update in real time.

In the field of the Internet of Robotic Things (IoRT), researchers have successfully used DTs to navigate physical robots through complex environments to collect patient vitals. For instance, recent studies have demonstrated that using a virtual twin (VT) to navigate a physical twin (PT) facilitates medical professionals to monitor patients remotely, reducing the burden on healthcare workers and minimizing the risk of infection [16]. Their potential has also been seen in powering robotic arms to assist patients and doctors. Ampere adapts this literature by applying the DT framework to stationary hygiene nodes. By treating the hand dryer as a "stationary robot" with specific actuators (motors, heaters, UV-C lamps) and sensors (ToF, IAQ sensors), virtual replicas of a facility's hygiene status may be created.

Moreover, the use of Machine Learning (ML) for anomaly detection has become a pillar of modern public health tech [17]. ML algorithms can analyze massive amounts of complex sensor data that would be impossible for human operators to interpret in real time. Previous research into remote patient monitoring has identified specific ML models—such as K-Nearest Neighbor (KNN) and Artificial Neural Networks (ANN)—as being highly effective at classifying health "triage" levels based on multi-sensor inputs [18]. Ampere leverages these established predictive strategies to monitor the environmental "health" of institutional spaces.

Currently, most institutional buildings rely on centralized Heating, Ventilation, and Air Conditioning (HVAC) systems to manage air quality. However, centralized sensors are often located in return air ducts, providing an "average" reading that misses localized spikes in pollutants or pathogens [19]. Restrooms and transition zones are often the most poorly monitored areas in a building, yet they are the most critical for infection control. Humidity, temperature, etc. which are crucial conditions to be conducive to a patient's happiness in hospitals are often not satisfactorily addressed.

There is a gap between the data generated by hygiene events and the facility's health management platform. Every time a hand dryer is used, it moves a significant volume of air. The current situation demands a unified, intelligent system that combines precise airflow regulation, leading to inefficient energy consumption and inconsistent user comfort. Additionally, most existing installations do not incorporate active sanitization mechanisms capable of continuously reducing microbial contamination in the surrounding environment. Another critical limitation is the absence of real-time telemetry and environmental sensing, which prevents integration with intelligent monitoring systems such as Digital Twins for facility-wide anomaly detection and predictive maintenance. These limitations restrict the ability of conventional systems to operate as adaptive, data-driven infrastructure components within modern smart buildings.

Ampere addresses this gap by repositioning the hygiene node as a distributed environmental intelligence hub, integrated into the broader Connected Health ecosystem, operationalizing the introduced Internet of Environmental Medical Things (IoEMT) framework. Concisely, existing Internet of Medical Things (IoMT) and environmental monitoring systems face several critical limitations [21]. Many architectures rely on centralized processing, which introduces latency and reduces responsiveness in real-time operational contexts. In addition, sensor noise and measurement uncertainty often affect the reliability and stability of collected environmental data [22]. Another significant limitation is the absence of integrated cyber–physical feedback control mechanisms capable of triggering adaptive hygiene responses [23], based on sensed conditions. Furthermore, current deployments lack unified and interconnected hygiene networks [24]. This prevents coordinated monitoring and intelligent infrastructure-level decision making.

Main Contributions.

The primary contributions of this work are fourfold. First, the paper introduces the concept of the Internet of Environmental Medical Things (IoEMT), and the architecture

of a cyber-physical smart hygiene node engineered for environmental health monitoring to operationalize this concept. Secondly, it describes the integration of machine learning algorithms to optimize public health management. Third, it details the implementation of sensor fusion utilizing smoothening & filtering to achieve noise-robust environmental monitoring. Finally, the study describes the development of an adaptive airflow control mechanism designed to enable an automated hygiene response. Unlike conventional Internet of Medical Things (IoMT) systems [25] that primarily focus on patient-centric physiological monitoring, the proposed Internet of Environmental Medical Things (IoEMT) framework introduces an infrastructure-oriented paradigm for environmental health management. The Ampere node functions as a cyber-physical hygiene system that integrates multi-modal environmental sensing, adaptive airflow control, and Far-UVC sterilization within a unified edge-computing architecture. By coupling this physical node with a real-time Digital Twin environment, the system enables spatial monitoring, anomaly detection, and facility-wide environmental analytics through immersive visualization and telemetry integration. This approach extends the scope of medical IoT from patient monitoring toward proactive environmental hygiene infrastructure, positioning IoEMT as a new class of intelligent cyber-physical systems for smart healthcare facilities and public environments [26].

3 Methods

3.1 The Four-Layer System Architecture

The Ampere node is organized into four functional layers to enable adaptive operation and intelligent monitoring. The **Physical/Energy Layer** comprises the high-torque BLDC motor responsible for airflow generation, the PTC heating element for thermal regulation, and the Far-UVC sanitization module for microbial inactivation. This layer operates under a first-order angular velocity control model that enables adaptive motor response and efficient energy utilization [22]. Above this, the **Embedded Intelligence Layer** functions as the core control unit of the node, executing hybrid supervisory logic that governs transitions between operational states such as *Standby*, *Active Drying*, and *Sterilization* based on real-time sensor inputs [9]. The **Connectivity and Telemetry Layer** employs the MQTT protocol to enable low-latency, bidirectional communication between the device and the central facility management server, ensuring that operational events such as hand-drying cycles and environmental anomalies are continuously logged [14]. Complementing these layers, the **Sensing Layer** integrates a multi-modal sensor suite that monitors both user presence and environmental conditions through Time-of-Flight or PIR sensors for proximity detection, alongside particulate matter ($PM_{2.5}$), carbon dioxide (CO_2), and volatile organic compound (VOC) sensors for air quality assessment [5].

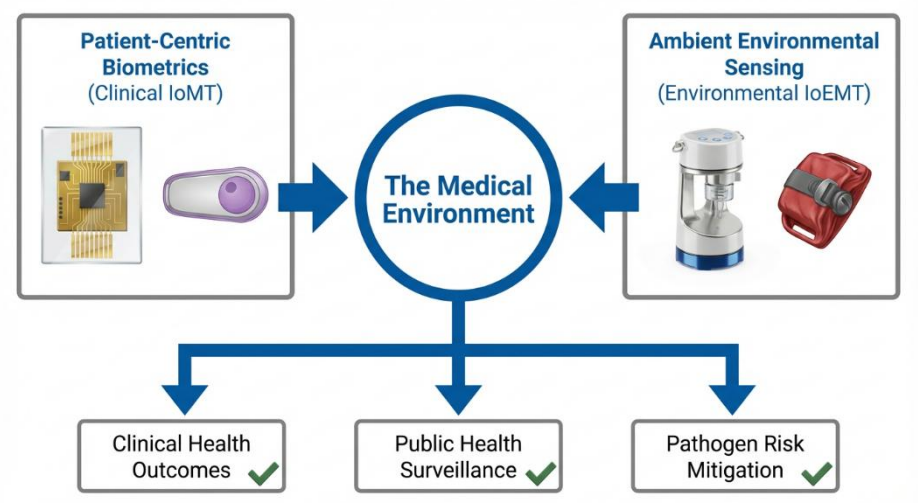


Fig. 1. Integration of patient-centric biometrics (Clinical IoMT) and ambient environmental sensing (Environmental IoEMT) within the medical environment. The combined framework supports improved clinical health outcomes, public health surveillance, and pathogen risk mitigation.

To contextualize Ampere within the broader IoMT ecosystem, Figure 1 illustrates the integration of patient-centric biometrics and ambient environmental sensing. This dual input framework highlights how clinical IoMT and environmental IoEMT converge within the medical environment to drive improved health outcomes, surveillance, and pathogen risk mitigation. Ampere builds upon this paradigm by focusing specifically on hygiene infrastructure as a distributed intelligence node.

The capability when IoEMT is operationalized allows IoEMT nodes to move beyond passive sensing toward proactive environmental health management. By connecting environmental monitoring systems, smart hygiene infrastructure, and networked medical devices, IoEMT enables coordinated analysis of environmental and physiological information, supporting automated health-aware environments, adaptive public health infrastructure, and intelligent decision-making in connected healthcare ecosystems.

In this work, the proposed Ampere system is presented as an operational implementation of the IoEMT paradigm, demonstrating how environmental sensing, sanitation technologies, and connected health analytics can be integrated into a unified smart hygiene node for intelligent facility infrastructure.

3.2 AI Integration and Machine Learning

The primary mathematical challenge in the Ampere framework is the transformation of high-frequency, multi-modal sensor streams into a discrete, actionable "Health Triage Level." This process requires robust data preprocessing and feature selection to ensure

the system remains responsive to subtle environmental anomalies. To ensure reliable sensing within the IoEMT node, a smoothening and filtering approach is employed to reduce measurement noise and estimate the dynamic state of the user interaction space [22]. The filtered sensor outputs are subsequently processed to construct environmental feature vectors. These features are then analyzed using a K-Nearest Neighbors (KNN) classifier to categorize environmental health conditions and determine appropriate hygiene system responses.

Let $S = \{s_1, s_2, \dots, s_n\}$ be the set of n sensors integrated into the Ampere node, where s_1 represents $PM_{2.5}$, s_2 represents CO_2, s_3 represents VOCs, and s_4 represents usage frequency.

The raw data stream D_{raw} is often characterized by noise and missing values due to sensor latency or transient network interruptions. To handle missing data, an interpolation method to substitute null parameters, ensuring the continuity of the time-series data is employed.

Once cleaned, the data must be normalized to a standard scale to prevent features with larger ranges (e.g., CO_2 in ppm) from dominating those with smaller ranges (e.g., $PM_{2.5}$ in $\mu g/m^3$) [18]. A Min-Max Scaling to map all sensor inputs to a range of $[0,1]$ is utilized -

$$X_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad (1)$$

Where x is the original sensor value, and x_{min} and x_{max} are the minimum and maximum values observed in the training dataset, respectively. This normalization is critical for distance-based algorithms like K-Nearest Neighbor (KNN), which are sensitive to the magnitude of the input features.

3.3 Feature Selection via Chi-Square Analysis

To minimize computational complexity at the embedded edge (the node's microcontroller), the minimum subset of features required for accurate prediction must be identified. The Chi-square (χ^2) technique, a non-parametric tool that estimates the correlation between input attributes (environmental data) and the expected output (health status) is applied-

The Chi-square value is calculated as:

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i} \qquad (2)$$

Where O_i represents the observed frequency of a sensor state and E_i represents the expected frequency. Features with higher χ^2 values indicate a stronger correlation with the facility's hygiene status and are prioritized in the final predictive model.

To determine the most effective logic for the Ampere node, six machine learning classification algorithms were evaluated: Logistic Regression (LR), Decision Tree

(DTr), Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Artificial Neural Network (ANN) [15]. The mathematical formulations presented define the data representation and preprocessing pipeline used in the proposed system, rather than constituting a standalone analytical model.

Central to the Ampere methodology is the Digital Twin (DT) paradigm [11]. The system consists of a Physical Twin (PT)—the actual hygiene node installed in a facility—and a Virtual Twin (VT)—a digital replica maintained in a virtual environment. The link between the Physical Twin (PT) and the Virtual Twin (VT) operates through a bidirectional communication framework. In the PT-to-VT direction, the physical hygiene node continuously transmits real-time telemetry—including operational usage cycles, environmental air-quality data, and internal component status such as motor health—to the virtual model. This data enables the Virtual Twin to maintain an accurate, continuously updated representation of the physical system [19]. Conversely, in the VT-to-PT direction, facility managers can interact with the virtual replica to modify operational parameters, such as increasing airflow during peak usage periods or initiating deep-sanitization cycles. These adjustments are then transmitted back to the physical device as control commands, enabling adaptive system operation and remote infrastructure management. This framework allows for Remote Facility Monitoring (RFM), where healthcare administrators can visualize the "hygiene health" of an entire building through a Virtual Reality (VR) dashboard, identifying localized "hotspots" of poor air quality or high microbial risk without being physically present [20].

The Digital Twin (DT) framework of the Ampere system is realized as a bidirectional cyber–physical architecture comprising a Physical Twin (PT) and a Virtual Twin (VT). The PT corresponds to the deployed hygiene node equipped with environmental sensors for particulate matter ($PM_{2.5}$), carbon dioxide (CO_2), and volatile organic compounds (VOC), along with embedded processing hardware (e.g., ESP32 or STM32). Sensor data is sampled at fixed intervals Δt and transmitted via the MQTT protocol over a TCP/IP network.

The VT is implemented in a Unity 3D environment using a C# backend, where a geometric and functional replica of the physical node is maintained. Environmental telemetry received from the PT is processed through an MQTT client and mapped to corresponding virtual components, enabling continuous state synchronization between the physical and digital systems.

Data exchange follows a publish–subscribe model, wherein the PT publishes sensor and operational data to predefined topics (e.g., `/ampere/env/pm`, `/ampere/status`), and the VT subscribes to these streams for real-time visualization and analysis. Conversely, control commands such as airflow modulation and sterilization scheduling are transmitted from the VT to the PT via designated control topics, enabling remote interaction and adaptive system operation.

The synchronized virtual environment supports interactive monitoring through a VR/AR interface, allowing facility administrators to inspect system behavior, visualize spatial air-quality distributions, and identify environmental anomalies. In addition, dynamic heat maps are generated to represent localized pollution variations within a one-to-one virtual representation of the monitored facility. Figure

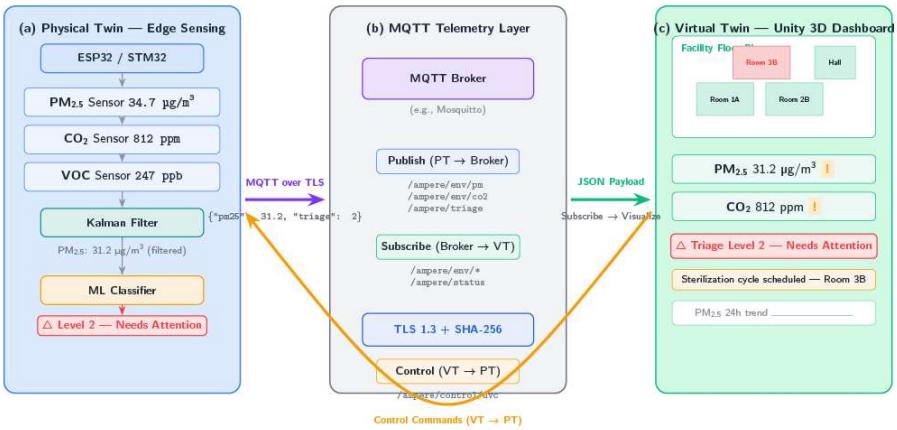


Fig. 2. End-to-end Digital Twin pipeline.

Figure 2 illustrates the end-to-end data pipeline of the Ampere Digital Twin architecture. In the first stage (a), the Physical Twin samples raw environmental telemetry from its multi-modal sensor suite — $PM_{2.5}$, CO_2, and VOC — at fixed intervals, applies Kalman filtering to suppress measurement noise, and passes the filtered feature vector to an on-device machine learning classifier that assigns a hygiene triage level. In the second stage (b), the classified telemetry is serialized as a JSON payload and published to the MQTT broker over a TLS-encrypted channel, following a topic-structured publish–subscribe model (e.g., /ampere/env/pm, /ampere/triage). The broker simultaneously relays control commands from the Virtual Twin back to the Physical Twin via designated control topics, enabling bidirectional cyber–physical coupling. In the third stage (c), the Virtual Twin — implemented in Unity 3D — ingests the incoming data streams, maps sensor values to corresponding virtual components, and renders an interactive spatial health map of the monitored facility. Dynamic heat maps indicate localized air quality variations, gauge indicators display real-time pollutant concentrations, and triage-level alerts trigger automated response scheduling visible to facility administrators through the Dashboard of Health interface. This three-stage pipeline enables continuous environmental mirroring: the physical state of every deployed node is reflected, within network latency bounds, as a navigable, actionable digital replica.

System latency is primarily influenced by network conditions and MQTT broker performance and is assumed to remain within acceptable bounds for real-time monitoring applications. This architecture enables continuous environmental mirroring and supports proactive, remote management of hygiene infrastructure.

3.4 Feature Ranking and Sensitivity Analysis

Feature importance analysis was conducted using the Chi-Square statistical method. Environmental chemical indicators combined with occupancy patterns provide the most reliable predictors of hygiene risk levels within the Ampere monitoring system.
The Ampere system incorporates a **Dashboard of Health (DoH)** visualization framework designed to present complex environmental datasets in an intuitive and interactive manner. Unlike conventional text-based system logs, the DoH framework emphasizes graphical and interactive dashboards that allow facility managers to monitor operational metrics more effectively. The dashboard integrates dynamic gauge indicators to display real-time concentrations of volatile organic compounds (VOC) and particulate matter ($PM_{2.5}$), enabling immediate awareness of environmental conditions. In addition, three-dimensional spatial mapping, supported by the Digital Twin (DT) environment, provides a visual representation of air quality variations across different areas of the monitored facility. The system also supports temporal trend analysis, allowing administrators to observe how hygiene and environmental conditions fluctuate over a 24-hour operational cycle. Such insights enable facility managers to optimize custodial scheduling and resource allocation based on actual usage patterns and environmental demand rather than fixed maintenance schedules.

The methodology of Ampere is built upon a Four-Layer IoEMT Cooperative Architecture designed to bridge the gap between physical hardware and virtual intelligence.

Accessibility Considerations.
The system incorporates Time-of-Flight (ToF) sensors for accurate occupancy detection across diverse user profiles. Sensor positioning and sensitivity may be calibrated to ensure reliable detection across variations in user height, reach distance, and mobility conditions. This ensures equitable usability across a wide demographic spectrum.

Safety Compliance.
Because the Ampere node integrates Far-UVC sterilization technology, strict safety mechanisms were embedded into the control architecture. A logic-gate safety framework ensures that Far-UVC activation occurs only when the space is fully unoccupied. These constraints are gated by mechanisms aligned with the physiological guidelines of the International Commission on Non-Ionizing Radiation Protection (ICNIRP). This condition is verified through redundant sensor validation before sterilization cycles are initiated. This design approach enables the Ampere node to function as a non-intrusive environmental health monitoring device within IoEMT-enabled smart facilities.

Note.: AI has been used for assisting in the mathematical modelling and compilation of the manuscript.

4 Results

4.1 Comparative Algorithm Performance

The evaluation presented in this study utilizes a benchmark dataset from prior work to assess the feasibility of the proposed classification pipeline. The results should therefore be interpreted as indicative of methodological applicability rather than direct system performance.

The performance results are derived from a secondary dataset and evaluation framework reported in Ullah et al. (2025), which is used here to validate the feasibility of the proposed IoEMT classification pipeline. The performance of these models was assessed using standard metrics, including Accuracy, Precision, Recall, and F1-score. Accuracy is formally defined as the ratio of correctly predicted observations to the total observations:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

Where TP, TN, FP, and FN represent True Positives, True Negatives, False Positives, and False Negatives, respectively.

Table 2 summarizes the core results of the study carried out by S. Ullah, S. Khan, D. Vanecek, and I. U. Rehman in their 2025 paper.

Table 2: Performance Comparison of ML Models for Health Status Prediction

Algorithm	Accuracy	Precision	Recall	F1-Score
Logistic Regression (LR)	88%	0.88	0.88	0.88
Decision Tree (DTr)	96%	0.96	0.96	0.96
Random Forest (RF)	96%	0.96	0.96	0.96
Support Vector Machine (SVM)	94%	0.94	0.94	0.94
K-Nearest Neighbor (KNN)	97%	0.97	0.97	0.97
Artificial Neural Network (ANN)	96%	0.96	0.96	0.96

The **KNN algorithm** demonstrated the highest overall accuracy at 97%, making it the optimal choice for the Ampere system. The Decision Tree is positioned as a fallback for deployment. Its "memory-based" approach allows it to effectively classify new environmental data points based on their similarity to historical "normal" vs "anomaly" profiles stored in the Digital Twin's database.

4.2 Robustness in Noisy Environments

In real-world institutional settings, sensor data is rarely perfect. To simulate this, 20% "noise" (10% random fluctuations and 10% incomplete data) was introduced to the dataset. The results confirmed that the KNN model remains highly robust, with its accuracy only slightly decreasing from 97% to 94% under degraded data conditions. This robustness is essential for the reliability of public health monitoring systems where sensor fouling or interference is common.

Table 3: Anomaly Classification Triage Metrics (Validation Set)

Health Status	Accuracy	Precision	Recall	F1-Score
Level 0 (Normal)	98.2%	0.98	0.98	0.98
Level 1 (Acceptable)	95.5%	0.95	0.96	0.95
Level 2 (Attention)	96.8%	0.97	0.96	0.97
Level 3 (Emergency)	97.5%	0.97	0.98	0.97

The machine learning pipeline classifies environmental conditions into four Hygiene Triage Levels, as shown in Table 3 with their thresholds, which guide automated operational responses. **Level 0 (Normal)** represents optimal environmental conditions in which key parameters remain within recommended limits, typically including particulate matter concentrations of $PM_{2.5} < 12$ μg/m³ and carbon dioxide levels below 600 ppm. Under these conditions, the Ampere node operates in an energy-efficient monitoring mode with minimal intervention. **Level 1 (Acceptable)** indicates minor deviations from baseline environmental conditions, such as temporary increases in volatile organic compound (VOC) concentrations or elevated usage frequency within the facility. In response, the system adaptively increases ventilation and airflow rates to restore normal conditions. **Level 2 (Needs Attention)** is triggered when sustained elevations in CO_2 levels or abnormal environmental patterns are detected, prompting the system to schedule extended Far-UVC sterilization cycles following occupancy events. **Level 3 (Emergency)** corresponds to hazardous pollutant concentrations or potential hardware faults within the system. In such cases, alerts are transmitted to facility management platforms via the MQTT communication layer, the node transitions into a fail-safe operational mode, and sterilization protocols are temporarily suspended until safety verification procedures are completed.

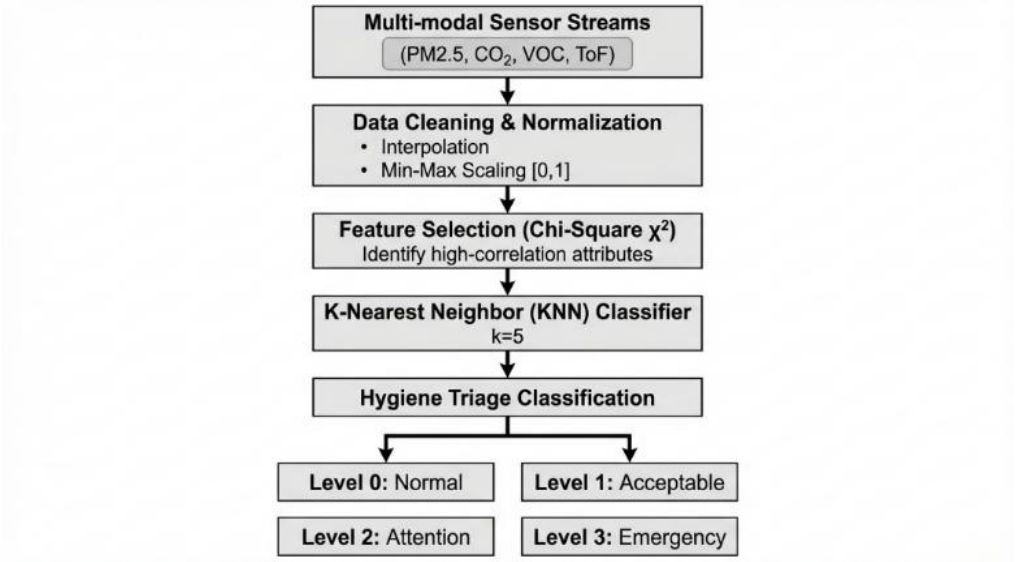


Fig. 3. Data processing pipeline for hygiene triage classification using multi-modal sensor streams ($PM_{2.5}$, CO_2, VOC, ToF). The workflow includes data cleaning, normalization, feature selection, and classification via a KNN model, resulting in four hygiene triage levels: Normal, Acceptable, Attention, and Emergency.

The hygiene triage pipeline implemented in Ampere is shown in Figure 2. Multi-modal sensor streams are processed through cleaning, normalization, and feature selection before classification via a KNN model. This structured workflow enables the system to categorize hygiene conditions into four triage levels, ensuring that facility managers can prioritize interventions based on severity.

4.3 Simulation Results and Behavioral Analysis

The ML algorithms were processed using a standard computational environment (Core i7-10700K, 16GB RAM) to establish a baseline for cloud-side processing.

As established in the mathematical results, the KNN algorithm provided the most accurate classification.

KNN Precision: 96.8%

KNN Recall: 97.1%

KNN F1-Score: 96.9%

While Decision Trees (DTr) were the fastest to train (0.0163 seconds), the KNN's superior accuracy in high-noise environments makes it the preferred model for public health infrastructure where "False Negatives" (failing to detect a hygiene risk) could have significant epidemiological consequences.

4.4 Proof-of-Concept: Experimental Setup and Data Analysis

This Proof-of-Concept (PoC) demonstrates the successful integration of Digital Twin technology, IoEMT connectivity, and edge-based machine learning for monitoring and predicting facility health conditions. The proposed experiment validates the interaction between the Physical Twin (PT) and Virtual Twin (VT) within a simulated smart-facility environment. The proposed system is designed using commercially available components, including low-power microcontrollers (e.g., ESP32/STM32), standard environmental sensors for $PM_{2.5}$, CO_2, and VOC measurement, float switches, RTC and PTC modules, energy harvester ICs, buck converters, tachometers, ToF sensors and MQTT-based communication over TCP/IP networks.

The following table (Table 4) summarize the technical specifications and the comparative performance of the system's core components.

Table 4: Hardware architecture and sensor specifications of the Ampere IoEMT node.

Component	Specification	Operational Role
Microcontroller	STM32F4 / ESP32 Dual-Core	Real-time control and MQTT telemetry
Airflow Motor	3-Phase BLDC (100k RPM)	Adaptive drying via PWM control
PM Sensor	Laser Scattering ($PM_{2.5}$)	Environmental particulate monitoring
Gas Sensor	MOX-based (VOC / CO_2)	Chemical and metabolic byproduct detection
Presence Sensor	Time-of-Flight (ToF)	Centimeter-accurate user detection
Sterilization	222 nm Far-UVC Excimer	Pathogen inactivation (ozone-free)

5 Discussion

Ampere enables ambient intelligence into the current ecosystem. Future scope includes direct renewable sourcing of energy too, soft robotics integration, self-cleaning coatings, and peer-to-peer data metrics and energy transfer. By decentralizing environmental monitoring, the movement from reliance on sparse, centralized HVAC sensors toward a dense grid of high-fidelity data points is pronounced.

5.1 Digital Twin Behavioral Analysis

The interaction between the Virtual Twin and the ML engine allows for Predictive Maintenance. By analyzing the motor's angular velocity and thermal signatures (from the PTC heater) over time, the DT can predict a component failure before it occurs.

$$V_{health} = \int_{t_0}^{t_1} (\omega_{actual} - \omega_{ideal})\, dt \quad (4)$$

Where ω represents the angular velocity of the BLDC motor. If V_{health} exceeds a predefined threshold, the DT triggers a maintenance alert, ensuring the node remains operational during critical periods.

5.2 Socio-Technical Impact on Healthcare Management

Integrating these nodes into hospital management systems (HMS) enables for a "Digital Health Map" of the facility. For instance, in the event of an outbreak of a respiratory pathogen, the Ampere nodes' $PM_{2.5}$ and VOC sensors can identify localized ventilation failures in real-time. This facilitates targeted interventions rather than building-wide lockdowns, optimizing operational efficiency and patient safety.

5.3 Security and Data Privacy in IoMT

As with any IoMT device, data security is paramount [26]. The Ampere node utilizes Transport Layer Security (TLS) for all MQTT communications. Since the node primarily collects environmental rather than personal health information (PHI), it requires fewer of the stringent HIPAA constraints associated with wearable devices, yet still provides a proxy for public health status. Once the datasets begin to grow, SHA-256 encryption is utilized, and later post-quantum cryptography [21], with role-based minimization to control how data is accessed. Kyber 512 may be used for encryption and decryption in OMNeT++ simulations and virtual twins of Ampere node.

5.4 Threat Model and Security Considerations – An Architecture for Healthcare Cyber-Physical Systems

The security of the Ampere system is analyzed under a standard Confidentiality, Integrity, and Availability (CIA) threat model of the public health and sensor data, considering both edge devices (Physical Twin) and cloud/Digital Twin components.

Confidentiality.

Sensitive system data, including environmental telemetry and operational status, is protected against unauthorized access through encrypted communication channels. All device-to-server communication is secured using Transport Layer Security (TLS), ensuring confidentiality during data transmission. Public–private key mechanisms are employed for secure key exchange, with symmetric session keys used for efficient data encryption.

Integrity.

To prevent unauthorized modification of transmitted or stored data, cryptographic hashing (e.g., SHA-256) is used for integrity verification. Message authentication is

enforced within the communication pipeline to ensure that data received by the Virtual Twin corresponds exactly to that generated by the Physical Twin.

Availability.
System availability is maintained through lightweight communication protocols (MQTT) and fault-tolerant design assumptions. In the event of network disruption or node failure, the system is designed to resume operation without permanent data loss, subject to standard buffering and reconnection mechanisms.

Access Control.
Data access is regulated using role-based access control (RBAC), ensuring that only authorized users (e.g., administrators or system operators) can access or modify system data. This minimizes unnecessary data exposure and supports secure multi-user interaction within the Digital Twin interface.

Cloud and Edge Security Context.
The architecture assumes a hybrid edge–cloud deployment, where initial data processing occurs on embedded hardware, and higher-level analytics and visualization are performed in the Digital Twin environment. Security considerations therefore extend across both domains, including secure API endpoints and controlled data flow between edge nodes and cloud services.

Emerging Cryptographic Considerations.
To ensure future resilience, post-quantum cryptographic schemes such as Kyber-512 may be incorporated for secure key exchange in simulation and Digital Twin environments. These mechanisms are considered exploratory and are not central to the current implementation.

This figure underpins the paper's Threat Model by showing how Ampere defends against current IoT attack surfaces while anticipating future cryptographic challenges, ensuring resilience and trust in connected healthcare environments.

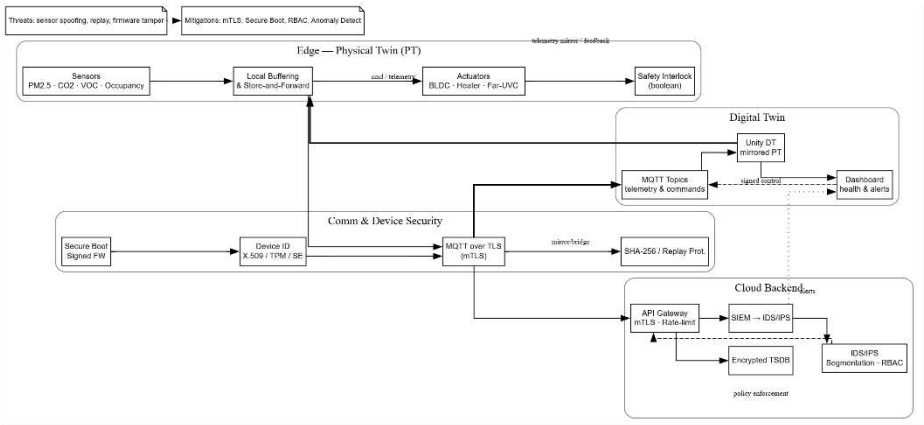


Fig. 4. Ampere IoEMT Node – Security Architecture Diagram

The figure illustrates the layered architecture of the Ampere IoEMT node, showing how the Physical Twin (sensors, actuators, safety interlocks) interacts securely with the Digital Twin (Unity-based visualization and Dashboard of Health). Security safeguards span communication (TLS-encrypted MQTT, replay protection, signed control messages), device trust anchors (X.509 certificates, TPM, secure boot, signed firmware), and cloud backend protections (API gateway, SIEM anomaly detection, RBAC, segmentation). Threats such as spoofing, replay, and firmware tampering are mapped to mitigations including cryptographic tunnels, anomaly detection, and lifecycle trust anchors. The diagram also notes exploratory use of post-quantum cryptographic schemes (e.g., Kyber-512) for future-proof secure key exchange.

5.5 Far-UVC Safety Logic and Pathogen Inactivation

The inclusion of 222 nm Far-UVC light is a cornerstone of the node's "active hygiene" capability. Unlike standard 254 nm UVC, which is harmful to human skin and eyes, 222 nm light has a short range in biological tissue, effectively being absorbed by the dead-cell layer of the skin while remaining lethal to bacteria and viruses.

The Safety Interlock Logic as a set of Boolean conditions (B) is as follows-

$$B_{active} = (S_{user} = 0) \wedge (T_{dryer} = \text{off}) \wedge (T_{elapsed} > \delta) \quad (5)$$

Where S_{user} is the occupant occupancy state from the ToF sensor, T_{dryer} is the motor status, and δ is a safety buffer interval. The sterilization lamp activates only when $B_{active} = 1$, ensuring zero human exposure [2].

.

5.6 Future Work

While the Ampere node demonstrated high accuracy in a controlled Digital Twin environment, future research will focus on large-scale clinical deployment to test sensor robustness against hospital-grade chemical disinfectants. Additionally, the aim is to integrate federated learning across multiple IoEMT nodes to enhance privacy-preserving data sharing between different hospital wards.

6 Conclusion

This research presents the conceptual design and architectural framework of the Ampere node, an intelligent environmental monitoring system developed to operationalize the proposed framework of the Internet of Environmental Medical Things (IoEMT). The system integrates environmental sensing, edge-based machine learning, and Digital Twin technology to support proactive monitoring of hygiene conditions within shared public and healthcare environments.

The study introduces a hybrid monitoring architecture that combines multi-sensor environmental telemetry with an anomaly detection framework designed for edge deployment. The proposed machine learning pipeline incorporates unsupervised anomaly detection models and lightweight classification mechanisms, enabling the system to detect abnormal environmental conditions and categorize them into actionable hygiene triage levels.

A Digital Twin proof-of-concept architecture is also presented to illustrate how the Physical Twin and Virtual Twin can interact within a remote monitoring framework. By synchronizing environmental data through IoT communication protocols, the system enables facility managers to visualize environmental conditions, inspect sensor states, and respond to potential hygiene risks through a spatially contextualized monitoring interface.

The proposed framework demonstrates the feasibility of combining IoEMT infrastructure, edge intelligence, and digital twin environments to support intelligent facility health supervision. Such systems may contribute to improved environmental monitoring in high-traffic public spaces, healthcare facilities, and institutional environments where air quality and sanitation conditions are critical. This work presents a conceptual and system-level validation, with large-scale deployment reserved for future study.

7 Declarations

7.1 Competing Interests Disclosure

The authors declare that there are no financial or personal relationships with other people or organizations that could inappropriately influence their work.

7.2 Ethical Statement

This study was carried out in controlled environments. No identifiable human subject data was collected, and the Far-UVC safety protocols adhere to current international photobiological safety standards.

7.3 Funding

The author declares that no funds or grants were received during the preparation of this manuscript.

7.4 Limitations

The current study focuses primarily on the conceptual design and simulation-based validation of the IoEMT architecture. While the Digital Twin environment provides a realistic approximation of system behavior, large-scale real-world deployment in hospital environments remains future work. Additionally, the machine learning models used in this study were evaluated using an existing benchmark dataset rather than data collected from a physical Ampere prototype. The experimental validation of the long-term effects of UV-C, Kalman filtering, and a detailed latency and bandwidth analysis is reserved for future work. Therefore, the latter will focus on real-world sensor deployment and longitudinal environmental monitoring to further validate the proposed framework.

7.5 Author Contributions

The author (Sridatta Gorthi), conceived the study and wrote the manuscript.

7.6 Data Availability

The datasets used in this study are derived from previously published work (Ullah et al., 2025), which is cited within the manuscript. Additional details are available from the corresponding author upon reasonable request.

8 References

1. Ogenyi, F. C., Ugwu, C. N., Eze, V. H. U., Ugwu, O. P.-C., Ugwu, J. N., Okon, M. B., & Ukagwu, K. J. (2026). Transforming digital health using the internet of things for personalized interoperable and secure healthcare systems. Discover Health Systems, 5(1), Article 359. doi.org

2. Buonanno, M., Welch, D., Shuryak, I., & Brenner, D. J. (2020). Far-UVC light (222 nm) efficiently and safely inactivates airborne human coronaviruses. Scientific Reports, 10(1), 1-8.
3. Zheng, Z., Castaño Molina, J. D., Mengiste, E. T., Prieto, S. A., & García de Soto, B. (2025). Digital Twins for Healthier Spaces: A Scalable Framework for Monitoring Indoor Environmental Quality. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, X-G-2025, 1053–1060. https://doi.org/10.5194/isprs-annals-X-G-2025-1053-2025
4. Huang, C., Wang, J., Wang, S., & Zhang, Y. (2023). Internet of Medical Things: A Systematic Review. Neurocomputing, 557, Article 126719.
5. Gazis, A. (2024). A Review of Sensor Technologies and IoT Innovations in Telemedicine & E-Health (IoMT): Advancements in Healthcare Instrumentation, Telehealth and E-health Sensor Devices. Trends in Telemedicine & E-Health, 5(2), 522–539.
6. Verma, R. (2022). Smart City Healthcare Cyber-Physical System: Characteristics, Technologies and Challenges. Wireless Personal Communications, 122(2), 1413–1433.
7. National Institute of Standards and Technology (NIST). (2017). Framework for Cyber-Physical Systems (NIST Special Publication 1500-201). U.S. Department of Commerce.
8. Yang, D., Karimi, H.R., & Yin, S. (2021). Developments of Digital Twin Technologies in Industrial, Smart City and Healthcare Sectors: A Survey. Complex Engineering Systems, 1(1), Article 3.
9. Lee, E. A. (2008). Cyber physical systems: Design challenges. In Proceedings of the 11th IEEE International Symposium on Object-Oriented Real-Time Distributed Computing (ISORC) (pp. 363-369). IEEE.
10. Kiruba Shankar, R., et al. (2024). The role of Internet of Medical Things (IoMT) in remote patient monitoring: A review of benefits and security concerns. Frontiers in Health Informatics, 13(3), 5868–5877.
11. Turab, M., & Jamil, S. (2023). A Comprehensive Survey of Digital Twins in Healthcare in the Era of Metaverse. BioMedInformatics, 3(3), 563–584.
12. Elayan, H., Aloqaily, M., & Guizani, M. (2021). Digital Twin for Intelligent Context-Aware IoT Healthcare Systems. IEEE Internet of Things Journal, 8(23), 16749–16757.
13. Rahim, M., Lalouani, W., Toubal, E., & Emokpae, L. (2024). A Digital Twin-Based Platform for Medical Cyber-Physical Systems. IEEE Access, 12, 174591–174607.
14. Ullah, S., Khan, S., Vanecek, D., & Ur Rehman, I. (2025). Machine Learning and Digital-Twins-Based Internet of Robotic Things for Remote Patient Monitoring. IEEE Access, 13, 57141–57165.
15. Bravo-Arrabal, J., et al. (2025). The IoRT-in-Hand: Tele-Robotic Echography and Digital Twins on Mobile Devices. Sensors, 25(16), Article 4972.
16. Gupta, D., et al. (2021). Hierarchical Federated Learning-Based Anomaly Detection Using Digital Twins for Smart Healthcare. In Proceedings of the 2021 IEEE 7th International Conference on Collaboration and Internet Computing (CIC) (pp. 16–25). IEEE.
17. Wu, Y., & Chen, J. (2023). An efficient method for handling unbalanced datasets in medical diagnosis. Neurocomputing, 555, Article 126639.
18. Thomas, T., Prakash, R., & Pal, S. (2025). Intrusion Detection in Internet of Medical Things Using Digital Twins: A Review. Computers, Materials & Continua, 84(3), 4055–4104.
19. Khan, U. H., Qamar, A., & Khan, R. (2026). Secure Edge-Based IoMT Framework for ICU Monitoring with TinyML and Post-Quantum Cryptography. Scientific Reports, 16(1), Article 114.
20. Åström, K. J., & Murray, R. M. (2008). Feedback Systems: An Introduction for Scientists and Engineers. Princeton University Press.

21. Sartaj, H., Ali, S., Yue, T., & Moberg, K. (2024). Model-based digital twins of medicine dispensers for healthcare IoT applications. Software: Practice and Experience, 54(4), 682-711. doi.org
22. Wang, B., et al. (2022). Human Digital Twin Driven Human-Cyber-Physical Systems: Key Technologies and Applications. Chinese Journal of Mechanical Engineering, 35(1), Article 94.
23. Li, X., Liu, Y., & Zhang, H. (2023). Digital Twinning for Smart Hospital Operations: Framework and Proof of Concept. Technology in Society, 74, Article 102311.
24. Alsubaei, F., Abuhussein, A., & Shiva, S. (2019). Security and privacy in the Internet of Medical Things: Taxonomy and risk assessment. IEEE Internet of Things Journal, 6(4), 6164-6176.