World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(Review Article)

Check for updates

A context-specific IoMT framework for energy-efficient remote monitoring of chronic patients in resource-limited settings

Abraham Isiaho [1,*], Kelvin Omieno [1] and Ayub Shirandula [2]

[1] Department of Computer Science, School of Computing and Informatics, Kaimosi Friends University, Kaimosi, Kenya.
[2] Department of Information Technology, School of Computing and Informatics, Kaimosi Friends University, Kaimosi, Kenya.

World Journal of Advanced Research and Reviews, 2026, 31(01), 533–544

Publication history: Received on 23 May 2026; revised on 05 July 2026; accepted on 09 July 2026

Article DOI: https://doi.org/10.30574/wjarr.2026.31.1.1806

Abstract

Remote monitoring of patients with chronic diseases can extend care beyond hospitals. However, most Internet of Medical Things (IoMT) frameworks assume that patients have stable electricity and internet connections and have high levels of digital literacy. These assumptions may not hold true in under-resourced communities. In response, we propose CARE-Lite IoMT, a context-specific framework for energy-efficient remote monitoring of chronic patients. The framework integrates low-power sensors, smartphone gateways, contextual sensing, community health worker support, interoperability, and secure communication. A design-science methodology was used to develop the framework through problem identification, literature-derived requirement specification, framework design, and scenario-based evaluation. Through scenario analysis, the system reveals that patient monitoring can be performed locally, and only information that reflects clinically meaningful changes can be sent to clinicians. Results from this developed framework show that energy efficiency should be regarded as a clinical safety requirement for remote monitoring systems rather than a secondary engineering consideration. The findings support IoMT designs based on low-power operation, offline resilience, actionable triage, interoperability, and secure data exchange.

Keywords: Internet of Medical Things; Remote patient monitoring; Chronic disease; Energy-adaptive monitoring; Edge-fog computing; Resource-limited settings; Community health workers

1. Introduction

Non -communicable diseases are a significant challenge to public health, particularly in the face of limited follow-up opportunities for afflicted individuals. According to the World Health Organization (WHO), non-communicable diseases (NCDs) are responsible for at least 43 million deaths each year, with the majority of these deaths occurring in low and middle-income countries [1]. Diseases like hypertension cause significant challenges to patients' health because they require the patient to be monitored continuously, yet the WHO reports that there are vast gaps in hypertension diagnosis, treatment, and control [2]. Digital health technologies provide opportunities to improve NCD management by strengthening continuity of care, interoperability, patient safety, and equitable healthcare delivery [3]

* Corresponding author: Abraham Isiaho

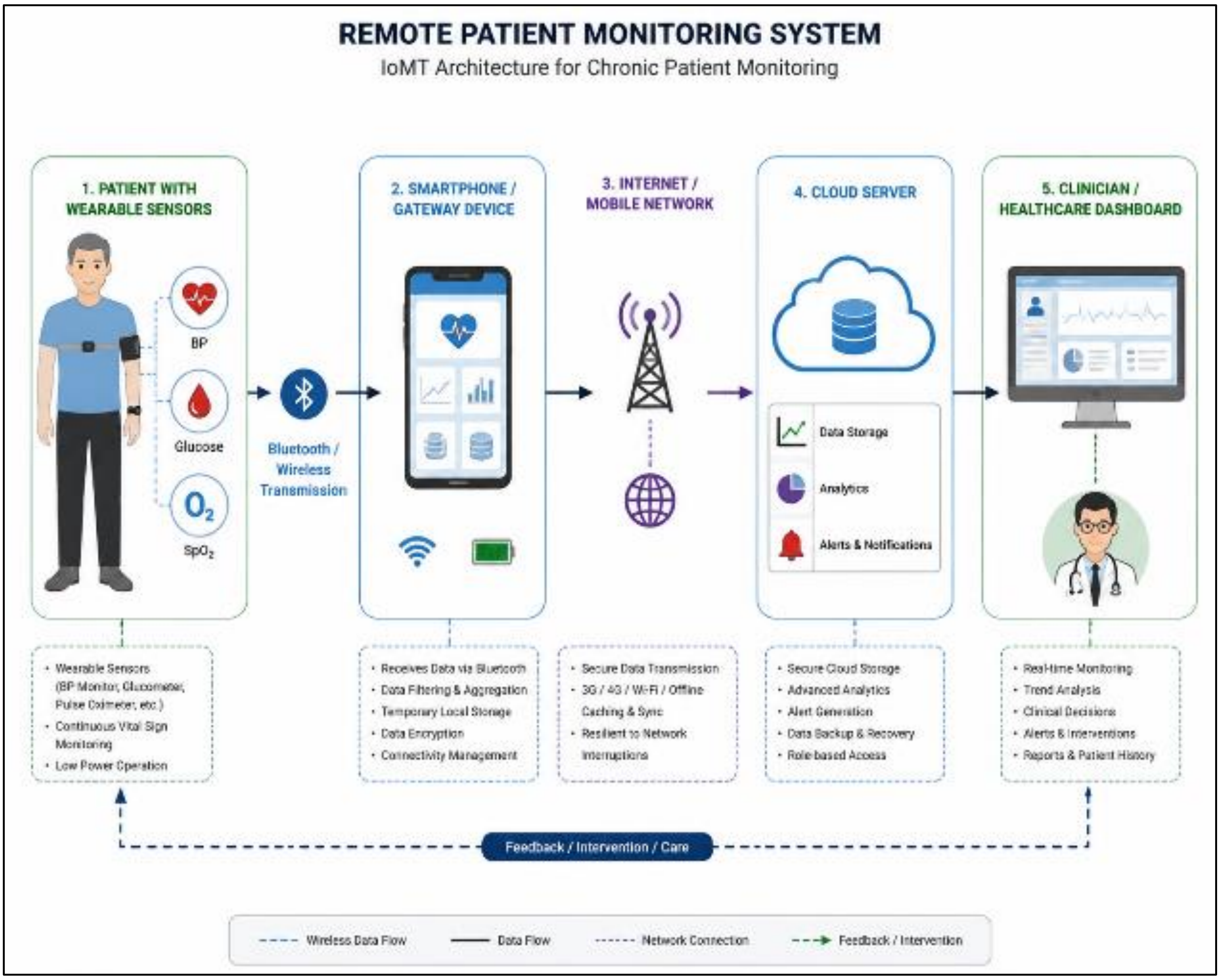

Figure 1 Remote patient monitoring architecture showing data flow from patient wearable sensors to clinician dashboard via mobile gateway and cloud system

Many remote health applications cannot connect to the internet, use prepaid mobile data plans for health data, and most health facilities do not have an electricity supply. According to the WHO, only 45% of health care facilities in Africa have electricity access [4]- [5].

The problem that is to be solved in this paper is that most IoMT frameworks for healthcare monitoring do not consider the energy constraints of resource-limited settings. Existing studies have explored IoMT architectures, remote patient monitoring, artificial intelligence, cloud, edge, fog, blockchain, wearable technologies, and analytics to improve healthcare monitoring systems [6] [7] [8]. However, there are few attempts to implement these technologies into an effective, energy-efficient monitoring system for patients with chronic diseases in resource-limited settings. This paper argues that IoMT systems should integrate energy conservation, offline resilience, patient safety, and interoperability as foundational design requirements rather than as later improvements.

The scientific contributions of this paper are as follows:

- The paper develops CARE-Lite IoMT, a context-specific framework-level artifact for energy-efficient remote monitoring of chronic patients in resource-limited settings. Unlike generic IoMT architectures, CARE-Lite integrates low-power sensing, smartphone or hub gateways, local analytics, fog synchronization, cloud/EHR interoperability, and CHW-supported triage into one operational framework.
- The paper introduces an energy-adaptive monitoring protocol that classifies patient monitoring into routine, warning, and emergency states. The protocol reduces unnecessary data collection and transmission during stable periods while enabling rapid escalation when clinically significant changes occur.

- The paper reframes energy efficiency as a clinical safety and equity requirement rather than a purely technical optimization. Energy-aware design supports patient protection because battery failure, unreliable networks, and excessive alerts can interrupt continuity of chronic disease management.
- The paper provides a scenario-based evaluation model comparing CARE-Lite with cloud-only RPM and generic edge-fog monitoring.

2. Literature Review

IoMT refers to the use of medical devices, sensors, mobile applications, and analytics to monitor medical patients and provide care. For patients with chronic conditions, IoMT permits monitoring at the patient's home instead of during clinic visits. Wearable devices have been studied as devices that permit for physiological monitoring of patients in real-time [9]- [10]. Furthermore, reviews of internet-based RPM have shown that such systems are beneficial in the management of chronic conditions, reducing the use of health services for those patients, and responding to potential emergencies [11].

Previous RPM studies have reported benefits such as improved safety, adherence, communication, and continuity of care, although concerns remain regarding workload, privacy, data accuracy, and technology adoption challenges [12]-[13]. Finally, telemedicine review studies have also reported that RPM is most beneficial when implemented within care pathways rather than as an independent technology [14] [15] [16].

Achieving these goals requires IoMT architectures that support local processing and reduce dependence on continuous cloud transmission. Mobile edge computing enables patient data to be analyzed closer to the source, reducing latency and communication requirements [17]- [18]. Other approaches, including federated learning and smart IoMT architectures, improve privacy protection and enable intelligent processing of healthcare data [19]- [20].

Furthermore, energy-efficient models of IoMT systems have been published. For instance, fog-cloud integration can reduce the amount of energy that telehealth IoT devices must expend, as well as the amount of data that must be processed by those IoT devices [21]. Task-offloading approaches have found that the central cloud server is not the best location for processing health information from patients with chronic conditions, instead, fog and edge computing servers may provide shorter response times and improved tracking of those patients [22]. Energy-aware placement of healthcare tasks across edge, fog, and cloud environments can further reduce energy consumption while improving response time and monitoring efficiency [23]- [24].

Another architecture that has been developed is the concept of a hybrid fog-edge architecture, which balances the latency, privacy, costs, and energy requirements of health monitoring systems [25]. Furthermore, telemedicine monitoring systems, which are based upon fog and edge computing, require a balance between response time, privacy, scalability, and cost of the technology [26]. However, technical performance alone is insufficient. Successful RPM implementation also depends on device ownership, electricity availability, internet access, healthcare workforce capacity, and digital literacy. Thus, a framework that incorporates these elements can better address the practical realities of resource-limited environments.

Another important element of IoMT systems is the concept of interoperability. IoMT platforms often rely upon standards for data sharing. For example, the HL7 FHIR standard has been established for the exchange of health data, and there are reviews of implementation guides for incorporating FHIR into the management of chronic diseases [27]. Furthermore, scoping reviews of interoperable IoMT platforms indicate the importance of standards, middleware, and health information exchange protocols [28].Open-source FHIR-based frameworks and ISO/IEEE 11073 standards support standardized exchange of biomedical information across devices and healthcare platforms [29] [30] [31] [32].

Additionally, data from IoMT systems is sensitive and often contains health-related and personal information about those patients. Furthermore, studies suggest that the digital transformation of health services require the use of IoT devices, but also introduces requirements for security [33]. Secure IoMT systems should minimize unnecessary data transmission, apply patient consent mechanisms, and enforce appropriate access controls [34]. Furthermore, security reviews of IoMT systems indicate requirements for security to applications and data to be able to be accessed by those patients and their healthcare providers, but to prevent unauthorized access to that information [35]. For instance, blockchain-IoMT systems have been published that introduce the concept of a tamper-proof IoMT system that is also interoperable with other health monitoring systems [36]. Furthermore, frameworks that utilize blockchain technology for remote monitoring and health applications enable trust between patients and their healthcare providers within the IoMT system [37]- [38]. Machine learning and federated learning approaches can further improve privacy by reducing dependence on centralized transfer of sensitive patient information [39]

Finally, while these technologies have significant benefits for patients with chronic conditions, their implementation into health systems and clinics requires consideration of various factors. For instance, while wearable-AI devices have been published and studied, other wearable device studies suggest benefits to using AI-enabled sensors to better understand the health of individuals, and to provide individualized care to each patient [40]- [41].Furthermore, early reviews of IoMT technology suggested that implementation of that technology does not necessarily result in the creation of a smart or effective health system [42] [43] [44].Thus, a framework that accounts for both technology as well as implementation factors can lead to successful implementation of IoMT technology for monitoring patients with chronic conditions [45].

The comparative review shows five main gaps in existing IoMT frameworks. First, many frameworks emphasize technical performance but insufficiently address electricity instability, charging limitations, and battery-related safety risks. Second, existing architectures often focus on data transmission while giving limited attention to alert fatigue, workload, missed readings, and human follow-up. Third, advanced AI, federated learning, and blockchain improve analytics and security but may introduce complexity unsuitable for initial deployment in low-resource clinics. Fourth, interoperability standards alone do not provide offline resilience, energy adaptation, or escalation mechanisms. Fifth, few frameworks explicitly integrate community health workers despite their importance in resource-limited chronic-care environments.

3. Materials and Methods

This paper used a design-science research methodology because its primary objective was to develop a framework-level artifact rather than a patient-level clinical trial or a deployed hospital information system**.** The study was therefore positioned as an artifact-development and analytic-evaluation study. The artifact developed in this paper is CARE-Lite IoMT, comprising four integrated outputs: a layered IoMT architecture, an energy-adaptive monitoring protocol, a requirements-to-design traceability matrix, and a scenario-based evaluation model. The framework was developed through problem identification, literature review, requirement specification, framework design, and scenario-based evaluation. Problem identification focused on the mismatch between conventional remote patient monitoring systems and the operational realities of resource-limited settings, especially unreliable electricity, intermittent connectivity, limited clinical staffing, low digital literacy, and fragmented health information systems. The literature review was used as a design input rather than as a background activity only. Evidence from IoMT, remote patient monitoring, edge-fog computing, interoperability, cybersecurity, chronic disease care, and rural health implementation was extracted and translated into system requirements. These requirements were then mapped to concrete design responses in CARE-Lite IoMT. The study addresses chronic-care challenges in resource-limited settings where distance, infrastructure limitations, device charging difficulties, connectivity problems, and workforce shortages restrict continuous monitoring.

The target population for this study includes adults with chronic medical conditions who are enrolled in primary care clinics or other health care programs. The use cases that are included in this study are patients with hypertension, diabetes, heart failure, chronic obstructive pulmonary disease(COPD), and those with a combination of the above conditions. The users of this framework were defined as patients with these conditions, their caregivers, community health workers, nurses, clinical officers, physicians, health information managers, and administrators for the health care programs. A resource-limited health care setting is one that experiences at least two of the following challenges: unreliable electricity supply, no internet access, limited health care workers, high cost to travel to the health care programs, low income in these communities, low health literacy, fragmented health records, or lack of capacity for the maintenance of medical devices in these clinics.

No patients, healthcare workers, or health facilities were recruited, and no clinical data were collected. Therefore, purposive scenario evaluation was used instead of statistical sampling because the objective was framework development rather than population estimation or clinical outcome testing. The scenario design evaluated three monitoring states (routine, warning, and emergency) and compared CARE-Lite against cloud-only and generic edge-fog architectures. Because the goal of this paper was to develop a framework rather than present the results of a clinical trial with human participants, no patient data was collected as a result of this study.

The requirements that were established for the framework were derived from the above health care literature. Each of these requirements was retained if it related to aspects like the safety of patients, energy efficiency of the framework, feasibility of the framework in weak health care infrastructures, or if it could be integrated into existing health information systems. The main design tool used in this study was a requirements-extraction and traceability matrix. This matrix linked each contextual problem to a design requirement and then linked each requirement to a CARE-Lite design response. For example, unreliable electricity was translated into low-power operation, adaptive sampling, sleep states, batch uploading, and battery-aware alerts. Intermittent connectivity was translated into offline caching, delayed synchronization, and SMS/USSD fallback. Limited clinical staffing was translated into three-state triage and community health worker task queues.

Table 1 Requirements-to-design traceability matrix for CARE-Lite IoMT

Requirement	CARE-Lite design response
Low power operation	Adaptive sampling, sleep states, battery-aware alerts
Offline resilience	Local caching and delayed synchronization
Clinical prioritization	Routine-warning-emergency triage
Interoperability	FHIR and device standards
Security and trust	Encryption, consent, access control
Usability	SMS/voice fallback and CHW support

For the analytic evaluation, the study used a scenario-evaluation template rather than a questionnaire. The evaluation variables included normalized device energy index, alert latency index, bandwidth demand index, clinician review burden index, and data completeness index. These variables were selected because they directly correspond to the problem domain of energy-efficient chronic patient monitoring in resource-limited settings. Device logs, battery discharge records, packet transmission records, alert logs, clinician workflow logs, and patient usability surveys are therefore not data already collected in this paper; they are proposed empirical validation measures for future field deployment. Validity was supported through requirement traceability, alignment between evaluation metrics and framework objectives, and transparent scenario assumptions. Since no questionnaire or participant instrument was used, psychometric reliability testing was not applicable.

Within the scenario-based evaluation, a framework based solely on the cloud was assigned baseline index of 100 for both energy and latency. A framework that utilizes fog computing was modeled as reducing the need for data transmission to the cloud. The CARE-Lite IoMT framework with CHW triage was modeled as further reducing the need for data transmission to the cloud and the need for repeated real-time transmission from the patients to the cloud. The normalized baseline approach enabled architectural comparison without dependence on specific devices, battery types, network providers, or infrastructure configurations. The cloud-only RPM comparator represented conventional centralized monitoring; the generic edge-fog comparator represented partial local processing; and CARE-Lite represented the developed model integrating context-aware sampling, offline caching, local triage, CHW support, and standards-based health data exchange.

4. Developed CARE-Lite IoMT Framework

Care-Lite IoMT was developed to provide the necessary chronic care monitoring while curbing the unnecessary layers of sensing, processing, communication, and clinician workload. CARE-Lite is presented as a framework-level prototype consisting of a layered IoMT architecture, an energy-aware monitoring protocol, a triage-and-escalation model, and interoperable data-exchange interfaces for future implementation. The framework considers four key aspects of chronic care: context-awareness, actionable alerts, resilient connectivity, and energy-light operation. These principles are operationalized through seven layers: patient sensing, gateway, context-aware energy management, local analytics, CHW task support, clinic fog processing, and cloud/EHR interoperability. The framework supports disease-specific sensor selection rather than requiring identical monitoring devices for all chronic conditions. The framework therefore supports disease-specific sensor selection, low-power data capture, Bluetooth Low Energy transmission where possible, gateway-based assessment, local caching, and escalation through the most reliable available channel. The security, governance, and consent layer cuts across all stages through encryption, role-based access control, audit logging, consent tracking, and minimal data transfer.

At the local analytics layer, small models for detecting abnormalities in the patients' readings are incorporated where appropriate. These models do not replace clinical judgement; rather, they operate as decision-support rules that classify readings into routine, warning, or emergency states. Disease-specific thresholds are configured by clinicians or programme protocols before deployment. The local analytics layer checks reading plausibility, abnormal trends, missed measurements, and possible false alerts caused by poor sensor quality. The CHWs assist patients who cannot manage the technology by monitoring for missed readings, repeated warnings, non-adherence to prescribed medications, battery problems, or failed escalation of critical alerts to the patients. The clinic fog and cloud/EHR layers support local dashboards, patient record summaries, analytics, and secure communication with healthcare institutions.

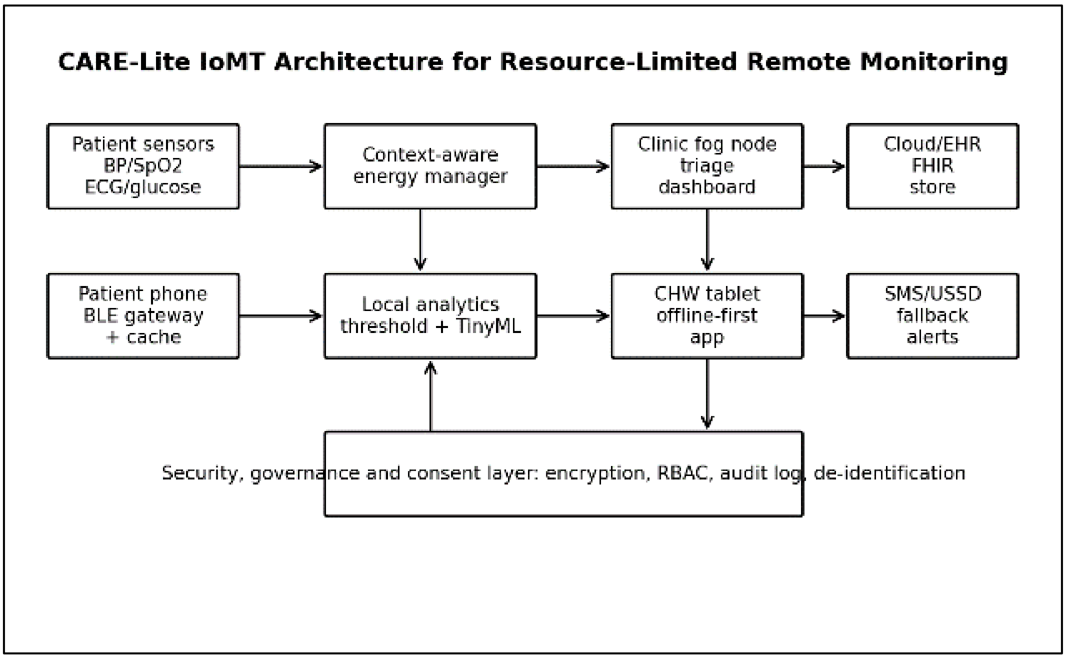

Figure 2 CARE-Lite IoMT architecture for energy-efficient chronic patient monitoring

The architecture shows how physiological data is captured, validated, cached, processed locally, escalated by urgency, and synchronized with the cloud/EHR layer only when clinically meaningful. CHW-supported workflows and offline resilience support continuity of care during connectivity disruptions.

Table 2 Framework components and main functions

Component	Core function	Energy-efficiency contribution
Sensor node	Captures vital signs and device status.	Uses sleep mode, scheduled sampling, BLE transmission.
Phone or hub gateway	Validates, encrypts, stores, and routes data	Reduces continuous cellular transmission
Energy manager	Selects routine, warning, or emergency state.	Reduces unnecessary sampling and transmission.
Local analytics	Detects abnormal trends and poor-quality readings	Filters unnecessary uploads
CHW dashboard	Prioritizes patients needing support or follow-up.	Reduces staff time spent scanning low-risk data.
Clinic fog node	Provides local processing and synchronization	Maintains operation during outages
Cloud/EHR service	Stores records and supports reporting	Receives summarized clinical information

The logic for operation of the system is adaptive monitoring. Each patient has a baseline risk assessment. Patient risk status is updated after each relevant reading. Routine states use infrequent compressed measurements, warning states temporarily increase monitoring, and emergency states trigger direct alerts to clinicians, CHWs, caregivers, or emergency pathways through app notification, SMS, USSD, or voice fallback. The energy manager evaluates data value, signal confidence, patient risk, connectivity, and available power before selecting the appropriate action.

The energy-adaptive monitoring protocol shown below is operationalized as Algorithm 1. The protocol classifies readings into routine, warning, and emergency states using clinical thresholds, battery level, connectivity, signal quality, and baseline risk. Routine readings are cached and batch-synchronized, warning readings generate increased monitoring and CHW follow-up, and emergency readings trigger immediate escalation through the most reliable available channel.

Algorithm 1. CARE-Lite energy-adaptive monitoring and escalation protocol
Input: Patient reading, timestamp, signal-quality flag, battery level, network status, baseline risk category, disease-specific clinical thresholds.
Output: Routine storage, warning task, emergency escalation, or updated sampling policy.
Begin **Step 1:** Acquire the patient's physiological reading and device-status information. **Step 2:** Check signal quality. If the signal is poor, request repeat measurement or generate a CHW support task. **Step 3:** Check battery level and network availability. If power or connectivity is low, prioritize local storage and low-energy communication. **Step 4:** Compare the reading with the patient's disease-specific threshold and recent trend. **Step 5:** Classify the reading into one of three states: routine, warning, or emergency. **Step 6:** For routine readings, store locally, compress, and batch upload when connected. **Step 7:** For warning readings, increase sampling temporarily, run a local trend check, and add the patient to the CHW review queue. **Step 8:** For emergency readings, send immediate alerts to the clinician, CHW, caregiver, or emergency pathway through app notification, SMS, USSD, or voice fallback. **Step 9:** Update the patient's monitoring state, care-plan flag, and future sampling policy. **Step 10:** Synchronize summarized data with the clinic fog node and cloud/EHR system when connectivity permits. *End*

5. Results

The primary result of the CARE-Lite framework was the artifact itself: the context-specific design of the IoMT framework. Consistent with the design-science methodology, the results are presented in two forms. The first result is the developed design artifact, namely the CARE-Lite IoMT framework, its layered architecture, its energy-adaptive monitoring protocol, and its implementation interfaces. The second result is the analytic scenario-based evaluation of the artifact against two comparator architectures. The findings represent framework-evaluation outputs based on scenario assumptions and normalized scoring rather than clinical trial or questionnaire outcomes. A secondary result is a scenario-based comparison of the system with two existing designs for IoMT systems: cloud-only RPM and generic edge-fog monitoring systems. Cloud-only RPM systems typically transmit all patient readings to a remote server in the cloud. Generic edge-fog monitoring systems reduce the amount of raw data that is transmitted from patients' devices to an edge or fog server but do not necessarily implement any context-aware adaptation of monitoring parameters based on the patient's risk factors. The CARE-Lite framework includes context awareness, event-driven monitoring, CHW triage, and offline monitoring features.

The scenario evaluated 100 patients with chronic conditions monitored over a 30-day period. Patients were assumed to exhibit normal, warning, and emergency readings for their conditions, with the majority of their readings being normal. The hypothetical cohort of 100 patients was used as a normalized scenario unit rather than as an empirical sample. It allowed the three architectures to be compared under the same workload conditions. The 30-day period was selected because monthly follow-up is common in chronic disease monitoring programme and is long enough to represent routine readings, missed readings, warning events, connectivity gaps, and escalation events. Energy consumption represented as a normalized index since many patient devices were having different sensor brands, phone battery types and charges, network strengths, and even the requirements of transmitting their chronic condition data. The effect that was measured from the CARE-Lite framework is the reduction in energy consumption of the patients' devices. Table 4 includes the assumptions that were made for this scenario evaluation.

Table 3 Scenario-based evaluation assumptions

Parameter	Cloud-only RPM	Generic edge-fog model	CARE-Lite IoMT model
Monitoring policy	Fixed sampling schedule for all patients.	Fixed schedule with local pre-processing.	Risk-, battery-, and network-aware adaptive sampling.
Connectivity assumption	Frequent cloud upload required.	Gateway or fog pre-processing available.	Offline cache with delayed sync and SMS/USSD fallback.
Alert handling	Cloud dashboard generates most alerts.	Fog node screens selected alerts.	Three-state local triage plus CHW task queue.
Data exchange	Vendor dashboard or cloud database.	Partial integration.	FHIR observations and device metadata.
Security posture	Cloud access controls.	Gateway plus cloud controls.	Minimal data transfer, encryption, Role-Based Access Control(RBAC), audit log, consent tracking.

Performance indices were calculated using a normalized weighted scoring approach. Cloud-only RPM was assigned a baseline score of 100, and alternative architectures were compared against the same evaluation dimensions. For lower-is-better metrics, the normalized index was calculated as follows:

Normalized index = Σ(weight of evaluation component × component score).

A lower score indicates lower energy demand, shorter alert latency, lower bandwidth demand, or lower clinician review burden. For data completeness, a higher score indicates better retention and recovery of readings during connectivity interruptions. The scoring components and weights were selected according to the design requirements established earlier in the paper: low-power operation, offline resilience, clinical prioritization, interoperability, security, and usability. The normalized indices combined component-level scores for sampling load, transmission demand, processing requirements, escalation delay, and data recovery performance.

Table 4 Scenario-based performance outputs, normalized to cloud-only RPM baseline

Metric	Cloud-only RPM	Generic edge-fog	CARE-Lite IoMT	Interpretation
Daily device energy index	100	74	58	CARE-Lite reduces radio use and repeated cloud uploads.
Alert latency index	100	68	41	Local triage and SMS/USSD fallback reduce delay for abnormal readings.
Bandwidth demand index	100	62	45	Batch synchronization and summarization reduce transmitted data.
Clinician review burden index	100	71	52	CHW and rule-based queues suppress low-value normal readings.
Data completeness index	82	88	93	Offline caching reduces missed readings during connectivity failures.

The results show that CARE-Lite achieved improved performance across all evaluated dimensions. The daily device energy index decreased from 100 in cloud-only RPM to 58 in CARE-Lite, indicating reduced sensing and communication demand through adaptive monitoring and batch synchronization. Alert latency decreased to 41 because abnormal readings can be processed locally and escalated without waiting for continuous cloud availability. Bandwidth demand decreased to 45 due to local validation and selective transmission.

CARE-Lite also reduced clinician review burden by filtering routine readings and prioritizing actionable cases through CHW-supported triage. Data completeness improved to 93 because offline caching and delayed synchronization reduced information loss during connectivity interruptions. These findings suggest that combining energy-aware computing with clinical workflow support provides advantages over conventional cloud-only and generic edge-fog approaches.

6. Discussion

The developed framework positions the aspect of energy efficiency as part of the safety of the medical devices. In the case of medical monitoring devices, a battery failure would prevent the monitoring of critical medical values. Thus, energy efficiency is associated with aspects like safety, equity, trust, and workload. CARE-Lite therefore reframes energy efficiency as a continuity-of-care requirement rather than a secondary technical optimization. Additionally, because many of the intended medical monitoring devices need to be implemented in rural health facilities, the energy requirements of the devices need to be considered [46].

Compared to cloud-only RPM, CARE-Lite reduces the dependency on the internet connection. This is beneficial in areas with poor connectivity or where patients must turn off their mobile data to save money. CARE-Lite changes this logic by allowing readings to be validated, cached, classified, and acted upon locally before cloud synchronization occurs. This reduces unnecessary radio use, minimizes repeated uploads of normal readings, and preserves escalation capacity for clinically meaningful events. The interoperability among RPM systems using IEEE 11073 and ZigBee standards allows for end-to-end monitoring of patients with RPM devices [47]. Furthermore, smart-home and fog-assisted healthcare models have shown that placing systems near the patient reduces the dependency on the cloud to operate [48]. CARE-Lite also improves on the current edge-fog model by considering the patient's data when processing the information from the RPM devices to recognize abnormal values before sending them to the cloud. Generic edge-fog systems can reduce latency and bandwidth, but they may still depend on fixed sampling schedules and may not include CHW-supported workflows. CARE-Lite adds patient risk state, battery status, network status, signal quality, missed-reading detection, and CHW task routing to the monitoring process.

The interoperability of the system is another benefit of CARE-Lite. Most current RPM models operate within isolated software dashboards. If their health data cannot be transferred into medical records, the doctors may not use that information to treat those patients. Using standards such as FHIR observations, ISO/IEEE 11073, and other internationally recognized healthcare data models allow the RPM system to be integrated with existing medical records systems. Early models require summaries of health data in CSV and PDF files, while more developed models can use FHIR application programming interfaces to automatically update medical records.

This study addresses an important gap by combining energy-aware operation, connectivity resilience, and clinical workflow support within one framework. Therefore, the discussion supports the central argument of the paper: CARE-Lite advances IoMT design by linking energy efficiency, offline resilience, local triage, interoperability, and human-supported chronic care into one coherent framework for resource-limited settings.

7. Conclusion

IoMT-enabled remote monitoring of patients with chronic diseases has strong potential to improve care delivery in resource-limited settings, but success depends on addressing energy, connectivity, staffing, and infrastructure constraints. This paper developed CARE-Lite IoMT as a context-specific framework-level artifact for energy-efficient remote monitoring of chronic patients in such environments. The framework integrates low-power sensors, smartphone or hub-based gateways, context-aware energy management, local analytics, CHW-supported triage, clinic fog nodes, secure governance mechanisms, and standards-based health data exchange.

The second objective was achieved by developing the CARE-Lite layered architecture, which enables local processing, caching, triage, and selective synchronization of patient data without continuous cloud dependence. The third objective was achieved through an adaptive monitoring protocol that classifies patient states into routine, warning, and emergency levels to optimize energy use while ensuring timely clinical escalation. The fourth objective involved scenario-based evaluation, which showed that CARE-Lite reduces energy use, latency, bandwidth demand, and clinician workload while improving data completeness compared to cloud-only and edge-fog models.

Implications

The study has key implications. First, health systems should prioritize workflow and clinical decision needs over device sophistication when implementing IoMT systems. Second, device selection should prioritize energy efficiency, durability, offline capability, and interoperability. Third, Community Health Workers should be integrated into monitoring workflows to support patients with adherence, device use, and escalation processes. Fourth, interoperability and governance should follow standards such as FHIR and ISO/IEEE 11073 with strong security and minimal data transmission. CARE-Lite can be implemented in phases depending on available infrastructure. Initial deployments can start with basic devices and SMS-based alerts, with advanced features such as fog nodes, FHIR APIs, and federated learning added gradually.

Limitation

This study has limitations. First, results are based on scenario evaluation rather than real clinical deployment. Second, results may vary depending on devices, networks, and clinical settings. Third, incorrect threshold settings may affect safety in unstable patients. Fourth, model validation across diverse populations is required to avoid bias. Fifth, implementation must comply with local data protection and ethical regulations. Future work should validate CARE-Lite through simulation and pilot testing in real chronic-care settings

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] World Health Organization. Non communicable diseases. World Health Organization. Regional Office for Europe; 2011.

[2] World Health Organization. Global report on hypertension: the race against a silent killer. World Health Organization; 2023 Sep 19.

[3] World Health Organization, "Global Strategy on Digital Health 2020-2025," WHO, Geneva, Switzerland, 2021.

[4] World Health Organization. Universal water, sanitation, hygiene, waste and electricity services in all health care facilities to achieve quality care: global framework for action 2024-2030.

[5] Lukuyu J, Taneja J. Powering up in Africa: electricity demand stimulation to build inclusive economies, reduce inequality, and improve power system sustainability. Current Sustainable/Renewable Energy Reports. 2023 Mar;10(1):1-1.

[6] Mahmmod BM, Naser MA, Al-Sudani AH, Alsabah M, Mohammed HJ, Alaskar H, Almarshad F, Hussain A, Abdulhussain SH. Patient monitoring system based on internet of things: A review and related challenges with open research issues. IEEE Access. 2024 Sep 6;12:132444-79.

[7] Boikanyo K, Zungeru AM, Sigweni B, Yahya A, Lebekwe C. Remote patient monitoring systems: Applications, architecture, and challenges. Scientific African. 2023 Jul 1;20:e01638.

[8] Shaik T, Tao X, Higgins N, Li L, Gururajan R, Zhou X, Acharya UR. Remote patient monitoring using artificial intelligence: Current state, applications, and challenges. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery. 2023 Mar;13(2):e1485.

[9] Jafleh EA, Alnaqbi FA, Almaeeni HA, Faqeeh S, Alzaabi MA, Al Zaman K, Alnaqbi F, Almaeeni H, Alzaabi M. The role of wearable devices in chronic disease monitoring and patient care: a comprehensive review. Cureus. 2024 Sep 8;16(9).

[10] Tegegne MD, Niakan Kalhori SR, Haas P, Sobotta VM, Warnecke J, Deserno TM. Wearable devices for remote monitoring of chronic diseases: systematic review. JMIR mHealth and uHealth. 2026 Feb 11;14:e74071.

[11] Emaliyawati E, Ibrahim K, Kurniawan T, Fitria N, Songwathana P. A systematic review of internet-based remote patient monitoring systems for chronic disease management in Asian. Patient preference and adherence. 2025 Dec 31:2985-3000.

[12] Tan SY, Sumner J, Wang Y, Wenjun Yip A. A systematic review of the impacts of remote patient monitoring (RPM) interventions on safety, adherence, quality-of-life and cost-related outcomes. NPJ Digital Medicine. 2024 Jul 18;7(1):192.

[13] Serrano LP, Maita KC, Avila FR, Torres-Guzman RA, Garcia JP, Eldaly AS, Haider CR, Felton CL, Paulson MR, Maniaci MJ, Forte AJ. Benefits and challenges of remote patient monitoring as perceived by health care practitioners: a systematic review. The Permanente Journal. 2023 Sep 22;27(4):100.

[14] Khan A, Duncan D. Remote patient monitoring applications in healthcare: Lessons from COVID-19 and beyond. Electronics. 2025 Aug 1;14(15):3084.

[15] Liu Y, Wang B. Advanced applications in chronic disease monitoring using IoT mobile sensing device data, machine learning algorithms and frame theory: a systematic review. Frontiers in Public Health. 2025 Feb 21;13:1510456.

[16] Uddin R, Koo I. Real-time remote patient monitoring: a review of biosensors integrated with multi-hop IoT systems via cloud connectivity. Applied Sciences. 2024 Feb 25;14(5):1876.

[17] Awad AI, Fouda MM, Khashaba MM, Mohamed ER, Hosny KM. Utilization of mobile edge computing on the Internet of Medical Things: A survey. ICT Express. 2023 Jun 1;9(3):473-85.

[18] Bhattacharya P, Mukherjee A, Bhushan B, Gupta SK, Gadekallu TR, Zhu Z. A secured remote patient monitoring framework for IoMT ecosystems. Scientific Reports. 2025 Jul 2;15(1):22882.

[19] Yadav SA, Malik V, Sharma S, Singh SV, Saudagar AK, Mohamed HG, Hussen S. Federated learning with IoT-based remote patient monitoring for real-time chronic disease prediction. Journal of King Saud University Computer and Information Sciences. 2026 Mar 23.

[20] Dahan F, Alroobaea R, Alghamdi W, Hajjej F, Raahemifar K. A smart IoMT based architecture for E-healthcare patient monitoring system using artificial intelligence algorithms. Frontiers in Physiology. 2023 Jan 30;14:1125952.

[21] Guo Y, Ganti S, Wu Y. Enhancing energy efficiency in telehealth internet of things systems through fog and cloud computing integration: simulation study. JMIR biomedical engineering. 2024 Mar 6;9(1):e50175.

[22] Bhasker B, Kaliraj S, Gobinath C, Sivakumar V. Optimizing energy task offloading technique using IoMT cloud in healthcare applications. Journal of Cloud Computing. 2025 Feb 17;14(1):9.

[23] Hossam HS, Abdel-Galil H, Belal M. An energy-aware module placement strategy in fog-based healthcare monitoring systems. Cluster Computing. 2024 Sep;27(6):7351-72.

[24] Alatoun K, Matrouk K, Mohammed MA, Nedoma J, Martinek R, Zmij P. A novel low-latency and energy-efficient task scheduling framework for internet of medical things in an edge fog cloud system. Sensors. 2022 Jul 16;22(14):5327.

[25] Islam U, Alatawi MN, Alqazzaz A, Alamro S, Shah B, Moreira F. A hybrid fog-edge computing architecture for real-time health monitoring in IoMT systems with optimized latency and threat resilience. scientific reports. 2025 Jul 15;15(1):25655.

[26] He Q, Xi Z, Feng Z, Teng Y, Ma L, Cai Y, Yu K. Telemedicine monitoring system based on fog/edge computing: A survey. IEEE transactions on services computing. 2024 Dec 2;18(1):479-98.

[27] Gazzarata R, Almeida J, Lindsköld L, Cangioli G, Gaeta E, Fico G, Chronaki CE. HL7 Fast Healthcare Interoperability Resources (HL7 FHIR) in digital healthcare ecosystems for chronic disease management: Scoping review. International journal of medical informatics. 2024 Sep 1;189:105507.

[28] Seth M, Jalo H, Högstedt Å, Medin O, Sjöqvist BA, Candefjord S. Technologies for interoperable internet of medical things platforms to manage medical emergencies in home and Prehospital Care: Scoping Review. Journal of Medical Internet Research. 2025 Jan 23;27:e54470.

[29] Adochiei FC, Țoi FA, Adochiei IR, Argatu FC, Serițan G, Petroiu GG. HL7 FHIR-Based Open-Source Framework for Real-Time Biomedical Signal Acquisition and IoMT Interoperability. Applied Sciences. 2025 Dec 3;15(23):12803.

[30] Cristobal-Huerta A, Torrado-Carvajal A, Rodriguez-Sanchez C, Hernandez-Tamames JA, Luaces M, Borromeo S. Implementation of ISO/IEEE 11073 PHD SpO2 and ECG device specializations over bluetooth HDP following health care profile for smart living. Sensors. 2022 Jul 28;22(15):5648.

[31] Elkin PL, Brown SH. Fast healthcare interoperability resources (FHIR). InTerminology, Ontology and their Implementations 2023 Jul 20 (pp. 511-565). Cham: Springer International Publishing.

[32] Badawi HF, Laamarti F, El Saddik A. ISO/IEEE 11073 personal health device (X73-PHD) standards compliant systems: A systematic literature review. IEEE Access. 2018 Dec 14;7:3062-73.

[33] Ogenyi FC, Ugwu CN, Eze VH, Ugwu OP, Ugwu JN, Okon MB, Ukagwu KJ. Transforming digital health using the internet of things for personalized interoperable and secure healthcare systems. Discover Health Systems. 2026 Dec;5(1):20.

[34] Prabha P, Chatterjee K. Towards a robust data privacy framework for IoT based health monitoring system. e-Prime-Advances in Electrical Engineering, Electronics and Energy. 2025 Jun 1;12:100961.

[35] Shojaei P, Vlahu-Gjorgievska E, Chow YW. Security and privacy of technologies in health information systems: A systematic literature review. Computers. 2024 Jan 31;13(2):41.

[36] Othman SB, Getahun M. Leveraging blockchain and IoMT for secure and interoperable electronic health records. Scientific Reports. 2025 Apr 10;15(1):12358.

[37] Kongsen J, Chantaradsuwan D, Koad P, Thu M, Jandaeng C. A secure blockchain-enabled remote healthcare monitoring system for home isolation. Journal of Sensor and Actuator Networks. 2024 Feb 5;13(1):13.

[38] Isiaho A, Omieno KK, Rono H. Tele-care medical information systems security techniques: A critical review of the state of the art techniques.

[39] Prasad VK, Bhattacharya P, Maru D, Tanwar S, Verma A, Singh A, Tiwari AK, Sharma R, Alkhayyat A, Țurcanu FE, Raboaca MS. Federated learning for the internet-of-medical-things: A survey. Mathematics. 2022 Dec 28;11(1):151.

[40] Ghadi YY, Shah SF, Waheed W, Mazhar T, Ahmad W, Saeed MM, Hamam H. Integration of wearable technology and artificial intelligence in digital health for remote patient care. Journal of Cloud Computing. 2025 Jul 21;14(1):39.

[41] Patel B. The role of AI-integrated wearables in predictive healthcare: a scoping review. Journal of Medical Artificial Intelligence. 2026 Jan 1;9:26.

[42] Shajari S, Kuruvinashetti K, Komeili A, Sundararaj U. The emergence of AI-based wearable sensors for digital health technology: a review. Sensors. 2023 Nov 29;23(23):9498.

[43] Rashid Z, Folarin AA, Ranjan Y, Conde P, Sankesara H, Zhang Y, Sun S, Stewart C, Laiou P, Dobson RJ. Disease insight through digital biomarkers developed by remotely collected wearables and smartphone data. arXiv preprint arXiv:2308.02043. 2023 Aug 3.

[44] Kim KK, McGrath SP, Lindeman D. Improving Hypertension and Diabetes Outcomes with Digital Care Coordination and Remote Monitoring in Rural Health. arXiv preprint arXiv:2508.19378. 2025 Aug 26.

[45] Smedslund G, Østerås N, Hestevik CH. Effects of remote patient monitoring on health care utilization in patients with noncommunicable diseases: Systematic review and meta-analysis. JMIR mHealth and uHealth. 2025 Oct 1;13:e68464.

[46] Wal P, Wal A, Verma N, Karunakakaran R, Kapoor A. Internet of medical things–the future of healthcare. The Open Public Health Journal. 2022 Dec 30;15(1).

[47] Dwivedi R, Mehrotra D, Chandra S. Potential of Internet of Medical Things (IoMT) applications in building a smart healthcare system: A systematic review. Journal of oral biology and craniofacial research. 2022 Mar 1;12(2):302-18.

[48] Peyroteo M, Ferreira IA, Elvas LB, Ferreira JC, Lapão LV. Remote monitoring systems for patients with chronic diseases in primary health care: systematic review. JMIR mHealth and uHealth. 2021 Dec 21;9(12):e28285.

[49] Imasiku K. Comprehensive approaches to electrifying rural health facilities: Integrating renewable energy and financial mechanisms in Sub-Saharan Africa. Energy Strategy Reviews. 2025 May 1;59:101736.