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Health Man & Info Sci
2026, 13(4), 284–294

HMIS
Health Management and Information Science

Review Article

Application of IoMT in Remote Patient Monitoring: A Narrative Review

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Abstract:

Introduction: The rapid expansion of the Internet of Medical Things (IoMT) has created new opportunities for continuous patient monitoring outside traditional clinical settings. This narrative review examines the applications, technical architectures, clinical outcomes, and implementation challenges of IoT/IoMT-based remote patient monitoring (RPM) systems from 2018 to 2026.

Methods: Following a structured narrative review approach, reproducible searches were conducted across PubMed, Web of Science, Scopus, Embase, Cochrane Library, ProQuest, and Google Scholar for publications from January 2018 to March 2026. After duplicate removal and title/abstract screening, full texts were assessed against predefined inclusion and exclusion criteria. In total, 27 publications met the inclusion criteria and form the core evidence base; the 35-entry reference list also includes seven earlier publications cited for background and technical context and one methodological reference.

Results: IoMT is a rapidly maturing technology with promising clinical benefits, particularly for patient safety; however, quality-of-life outcomes remain mixed and cost-effectiveness evidence is not yet sufficient. Sustainable deployment requires data exchange standardization, security-by-design, clinical sensor validation, and user-centered design. Future research should prioritize long-term randomized controlled trials, health economic evaluations, and outcome assessments in diverse populations.

Conclusion: IoMT is a rapidly maturing technology with promising clinical benefits, particularly for patient safety; however, quality-of-life outcomes remain mixed and cost-effectiveness evidence is not yet sufficient. Sustainable deployment requires data exchange standardization, security-by-design, clinical sensor validation, and user-centered design. Future research should prioritize long-term randomized controlled trials, health economic evaluations, and outcome assessments in diverse populations.

Keywords: Internet of Things; Internet of Medical Things; Remote Patient Monitoring; Health Monitoring System; Wearable Sensors; Data Security; Artificial Intelligence; Cloud Computing

Article History:
Received: 3 August 2026
Accepted: 24 September 2026

Please cite this paper as:
Ehteshami A, Rezaei A, Esmailzadeh M. Application of IoMT in Remote Patient Monitoring: A Narrative Review. Health Man & Info Sci. 2026; 13(4): 284-294. doi: 10.30476/jhmi.2026.111783.1392.

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Introduction

The growing burden of chronic diseases such as diabetes, cardiovascular disease, and heart failure, alongside aging populations and increasing pressure on healthcare systems, has made the need for innovative out-of-hospital care solutions a global priority (1, 20. Remote Patient Monitoring (RPM) using the Internet of Things (IoT) and the Internet of Medical Things (IoMT) represents a technological response to this challenge (3). IoT-enabled RPM systems have demonstrated potential to reduce hospital

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readmissions, improve patient outcomes, and enable proactive clinical intervention (4).

IoT refers to a network in which physical objects are connected to each other and to the internet to collect and exchange data (5). IoMT is a specialized subset of IoT that interconnects medical sensors, devices, and software for healthcare purposes (6, 7). In the context of RPM, these technologies enable continuous collection of vital signs including heart rate, blood oxygen saturation, blood pressure, and blood glucose outside traditional clinical environments (8, 9).

In recent years, the development of low-cost, high-precision sensors; the expansion of wireless connectivity (Wi-Fi, Bluetooth, ZigBee, 5G); the growing capacity of cloud and edge computing; and advances in machine learning algorithms have collectively made RPM systems considerably more reliable, cost-effective, and intelligent (10, 11). The COVID-19 pandemic further accelerated the adoption of these technologies, highlighting the critical need for remote healthcare delivery (12).

Despite these advances, significant challenges remain in data security, system interoperability, integration with clinical workflows, sensor validation, and the digital divide (13, 14, 15). Moreover, despite a growing body of evidence, clinical outcome results remain heterogeneous and warrant critical appraisal (16).

The scale of this transformation is considerable. Chronic diseases now account for the majority of the global disease burden, and health systems face simultaneous pressure from aging populations, workforce shortages, and rising care costs. Remote patient monitoring offers a credible path to shifting care from reactive, hospital-centered episodes toward continuous, preventive, and patient-centered models, and it has consequently become a strategic priority for health systems worldwide. The COVID-19 pandemic further intensified this trajectory: with in-person care restricted, telehealth and remote monitoring moved from marginal innovations to mainstream channels of care delivery within months (12).

A growing body of review literature reflects this attention. Al-Turjman et al. systematically mapped intelligence trends in IoMT (3), while Monaghesh and Hajizadeh synthesized the role of telehealth during the COVID-19 outbreak (12). More recently, Tan et al. (16) provided a systematic review of RPM outcomes - safety, adherence, quality of life, and cost-related outcomes - during care transitions from inpatient settings to the home. Recent reviews have also mapped IoT applications in healthcare in general terms (2). However, most existing reviews concentrate on a single dimension - either technical architecture, or clinical effectiveness, or security - and few integrate all three with implementation considerations in a single synthesis.

The present narrative review was designed to address this gap by integrating the technical, clinical, security, and implementation dimensions of IoMT-based RPM in one coherent synthesis, with attention to the needs of health information management practice and to health systems similar to that of Iran. The remainder of the paper is organized as follows: Section 2 describes the review methodology; Section 3 presents the findings across architecture, sensors, communication, artificial intelligence, clinical outcomes, security, and implementation; Section 4 discusses the findings in relation to prior reviews and their implications; and Section 5 concludes with limitations and future directions.

This narrative review aims to synthesize and analyze available evidence on: (1) technical architectures of IoMT-RPM systems, (2) types of sensors and devices used, (3) documented clinical outcomes, (4) security approaches, (5) the role of artificial intelligence in data analysis, and (6) implementation challenges and strategies during the period 2018-2026.

Materials and Methods

Study Design

This study was conducted as a narrative review, integrating evidence across heterogeneous study designs and disciplines. Narrative review methodology was deliberately chosen over a systematic review or a scoping review because the research questions of this study are broad, multidimensional, and heterogeneous, spanning technical architectures, sensor and communication technologies, artificial intelligence methods, clinical outcomes, security approaches, and implementation challenges. A systematic review requires a narrow, pre-specified PICO question and homogeneous study designs, which would exclude most technical and implementation literature relevant to this topic; a scoping review maps the extent of literature without synthesizing findings in depth. A structured narrative approach, by contrast, permits thematic synthesis across heterogeneous evidence types while maintaining explicit search, screening, and inclusion procedures. The conduct of this review is informed by established narrative review guidance, which emphasizes explicit search strategy, transparent selection, and structured synthesis, without the formal PRISMA flow required for systematic reviews (for methodological background see Green et al. (17)).

Search Strategy

A comprehensive literature search was conducted across seven electronic databases: PubMed, Web of Science, Scopus, Embase, Cochrane Library, ProQuest, and Google Scholar. The search covered publications from January 2018 to March 2026. The following search string and its database-specific adaptations were used: ("Internet of Things" OR "IoT" OR "Internet of Medical Things" OR "IoMT" OR "healthcare IoT") AND ("remote patient monitoring" OR "patient monitoring" OR "remote monitoring" OR "health monitoring" OR "wearable sensors" OR "smart health"), combined where appropriate with technology-specific terms ("edge computing," "fog computing," "cloud computing," "machine learning," "artificial intelligence") and outcome-related terms ("clinical outcome," "patient safety," "security," "interoperability"). Google Scholar searching was limited to the first 200 relevant hits per search combination. In addition, the reference lists of included articles were manually screened to identify further relevant studies.

Inclusion and Exclusion Criteria

Inclusion criteria

Peer-reviewed original studies and systematic reviews/meta-analyses published between January 2018 and March 2026 (both constitute the core evidence base, with systematic reviews used primarily for clinical-outcome synthesis); earlier publications were consulted only for background or technical context and were not treated as part of the core evidence base

English or Persian language

Subject: IoT/IoMT-based patient monitoring systems

Contains extractable technical or clinical data

Exclusion criteria

Letters to the editor, editorials, commentaries, opinion pieces, and conference abstracts without available full text

Non-peer-reviewed sources, and studies focused exclusively on non-medical IoT applications or not addressing patient monitoring

Duplicate studies

Screening and Data Extraction

After initial searching, duplicate records were removed. Titles and abstracts of the remaining unique records were screened independently by two reviewers, with disagreements resolved through discussion and consensus. Full texts of potentially eligible studies were then assessed against the inclusion and exclusion criteria, and relevant data were extracted using pre-designed extraction tables. Extracted data included: system architecture, sensor types, communication protocols, data processing methods, clinical outcomes, security approaches, and study limitations. In total, 27 publications (original studies and systematic reviews) published between January 2018 and March 2026 met the inclusion criteria and, together with seven pre-2018 publications cited solely for background or technical context and one methodological reference, form the 35-entry reference list of this review (Table 1).

Within this core set, published systematic reviews (most prominently Tan et al. (16)) were used primarily for the synthesis of clinical-outcome evidence and therefore form part of the evidence base rather than serving only as contextual background. Consistent with narrative review methodology, no formal PRISMA flow diagram is reported; however, the number of studies finally included is stated here for transparency. Publications predating 2018 that appear in the reference list are cited solely as background or technical context and were not included in this count.

Results

Summary of Key Findings from Reviewed Studies

Table 1 presents a summary of the principal IoMT-RPM systems reviewed in this study, including their technical specifications, clinical applications, and reported outcomes.

Table 1. Summary of IoMT-RPM Systems Reviewed in This Study

Ref	Author/Year	Architecture	Sensors	Communication	Application	Key Finding	Security
[8]	Kumar (2020)	IoT smart healthcare	ECG, SpO2, BP, Temp	Wi-Fi, BLE	Multi-disease	Healthcare 4.0	Encryption
[9]	Farahani (2018)	Fog-driven IoT	Multi-sensor	Fog, Cloud	Chronic disease	Reduced latency	Fog security
[18]	Kaur (2019)	Random Forest	ECG, SpO2, BP	IoT	Patient prediction	RF accuracy	Standard
[19]	Yacchirema (2019)	Ensemble ML	Accelerometer	IoT, Mobile	Fall detection	ML accuracy	Encryption
[20]	Zeshan (2023)	Ontology-based	Multi-sensor	Cloud, Edge	Remote monitoring	Interoperability	Ontology
[21]	Akkas (2020)	IoT platform	Vital signs	Wi-Fi, BLE	Patient monitoring	Architecture	Standard
[22]	Alsayaydeh (2023)	ESP8266/Arduino	Pulse, Temp, BP	Wi-Fi	Elderly	Real-time	IoT platform
[23]	Rahmani (2018)	Fog gateway	Multi-sensor	Edge/Fog	Smart e-health	Edge latency	Fog gateway
[24]	Damera (2025)	AI IoMT+Cloud	Biosensors	Cloud, WSN	Disease class.	98.62% accuracy	Cloud
[25]	Khan (2020)	Fuzzy Inference	Clinical params	IoT	COVID-19	~83% accuracy	Standard
[26]	Dwivedi (2019)	Blockchain	Health data	Decentralized	Secure records	Blockchain	Blockchain+ECC
[27]	Kapoor (2023)	Energy-efficient	Multi-sensor	Clustering	Secure monitoring	Lightweight cryptography + optimized clustering	Ciphertext
[28]	Banu (2021)	Big Data+IoT	Pulse, Temp, BP	Kafka	Vitals monitor	Spark analytics	Kafka

IoMT-RPM System Architecture

The majority of reviewed systems follow a standardized four-layer architecture (9, 10, 21):

Layer 1 - Sensing: Physiological data collection via wearable, adhesive, or stationary sensors. This layer is the direct point of contact with the patient. Common sensors include ECG, SpO2, blood pressure, temperature, and glucose monitors (8, 18).

Layer 2 - Communication: Wireless transmission of data through various protocols including Bluetooth Low Energy (BLE), Wi-Fi, ZigBee, LoRa, and cellular networks (4G/5G). Protocol selection is based on range, power consumption, and data transfer rate (11, 14).

Layer 3 - Processing and Storage: Comprises edge computing for preliminary processing and latency reduction, and cloud computing for storage, advanced analysis, and remote access. Machine learning algorithms operate at this layer (10, 18).

Layer 4 - Application: User interfaces including mobile applications, web dashboards, and alert systems that make processed data accessible to patients, caregivers, and clinical teams (9, 19, 29).

Recent advances have introduced ontology-based frameworks that enhance semantic interoperability across these layers,

enabling more intelligent data integration and reasoning (20).

Sensors and Wearable Devices

A broad range of sensors has been used across reviewed systems:

Cardiovascular sensors: ECG for cardiac rhythm monitoring and arrhythmia detection; MAX30102 pulse oximeter for simultaneous heart rate and SpO2 measurement; non-invasive blood pressure sensors. These sensors have been applied across cardiac, respiratory, and post-COVID-19 conditions (8, 25).

Metabolic sensors: Continuous Glucose Monitors (CGM) for diabetic patients, enabling ongoing measurement without invasive blood sampling (8).

Temperature sensors: Thermistors and body temperature sensors for fever and infection monitoring, which gained particular importance during the COVID-19 pandemic (12).

Motion sensors: Accelerometers and gyroscopes for physical activity assessment, fall detection, and rehabilitation monitoring (6, 29).

Multi-parameter systems: Advanced platforms integrating multiple sensors simultaneously, including pulse oximeters, ECG, temperature, and blood pressure sensors for comprehensive patient assessment (22).

Communication Technologies

Technology selection is use-case dependent:

Bluetooth Low Energy (BLE): Preferred for sensor-to-smartphone communication due to its short range and low power consumption (11).

Wi-Fi: Suitable for home and hospital environments with higher bandwidth requirements (14).

ZigBee: Used in mesh sensor networks for multi-patient monitoring (11).

LoRaWAN: Designed for remote areas requiring wide coverage (14).

5G Networks: With ultra-low latency, enable edge computing deployment and guarantee near-real-time data transmission (11, 14).

Fog Computing: Edge-fog architectures process data locally before cloud transmission, reducing latency and bandwidth requirements (23).

Machine Learning in IoMT Data Analysis

The integration of artificial intelligence with IoMT has been one of the most significant developments of this period:

Traditional Machine Learning: Classical algorithms remain the workhorse of IoMT analytics. The Random Forest algorithm has been applied in IoT-based health monitoring systems, demonstrating strong capability in patient status classification and detection of physiological anomalies from multi-dimensional sensor data (18). In a comparative evaluation of data-mining algorithms on IoT sensor data, Random Forest and comparable classifiers achieved accuracies of approximately 85-99% in classifying patient status (18).

Deep Learning Approaches: Long Short-Term Memory (LSTM) networks for time-series physiological data and anomaly detection algorithms for early warning (10, 19). Classical methods such as Support Vector Machines (SVM) are widely used for classification in this domain but are categorized here as traditional machine learning approaches rather than deep learning.

Transformer-Based Models: Recent advances include the Transformer-based Self-Attention Model (TL-SAM), which enhances disease classification by replacing conventional convolutional layers with transformer layers. This approach has achieved exceptional accuracy of 98.62%, precision of 97%, recall of 98%, and F1-score of 97% (24).

Fuzzy Inference Systems: IoMT-based smart monitoring hierarchical fuzzy inference systems have been developed for disease diagnosis, including COVID-19 detection with approximately 83% accuracy (25).

Types of RPM Interventions

Tan et al. (16) classified RPM interventions into seven categories: (1) communication tools, (2) computer-based systems, (3) smartphone applications, (4) web portals, (5) augmented clinical devices with

monitoring capabilities, (6) wearables, and (7) standard clinical tools for intermittent monitoring [16]. This taxonomy, derived from a systematic review of 29 studies from 16 countries, enables comparative analysis of the effectiveness of different intervention types.

A methodological clarification is required for the interpretation of the clinical evidence in Section 3.7. The scope of this review is IoMT-based RPM; however, much of the strongest clinical evidence - particularly the large systematic review by Tan et al. (16), published in npj Digital Medicine in 2024, - covers broader RPM interventions, including mobile applications, web portals, communication tools, and intermittent telephone-based monitoring, which do not necessarily involve connected medical sensors. In this review, findings are therefore interpreted as follows: where evidence derives from interventions with continuous biosensor data capture and networked transmission (for example, wearable ECG, SpO2, CGM, or accelerometer-based systems), it is treated as IoMT-specific; where it derives from general RPM modalities, this is stated explicitly. In Section 3.7, the safety, adherence, and quality-of-life synthesis of Tan et al. reflects the broader RPM evidence base, whereas the disease-specific applications in Section 3.9 draw predominantly on IoMT-specific studies.

Clinical Outcomes

Safety: The systematic review by Tan et al., covering 29 studies from 16 countries, reported statistically significant improvements in patient safety and reductions in adverse clinical events (16). These findings are consistent with results from independent studies reviewed here (19, 22).

Adherence: Results for treatment adherence were generally positive but heterogeneous. Tan et al. (16) reported that some studies showed significant improvements in medication and lifestyle adherence, while others found no significant difference compared to usual care.

Quality of Life: Across 14 studies examining quality-of-life outcomes, mixed results were reported. Outcome measures included the six-minute walk test, pulmonary function, physical and mental component scores, and dyspnea (16).

Cost-Effectiveness: Tan et al. concluded that, although a clear downward trend was observed in the risks of hospital admission/readmission, length of stay, number of outpatient visits, and non-hospitalisation costs, the available evidence does not yet establish the cost-effectiveness of RPM, and more economic evaluations are needed (16).

Security Approaches

Reviewed studies proposed multiple approaches to IoMT data security:

Encryption and Authentication: End-to-end encryption and multi-factor authentication are the most commonly used solutions (15, 30, 31).

Blockchain Technology: Blockchain has been proposed as a decentralized platform for secure, immutable storage of medical records (26).

Knowledge Graphs: Bughio et al. proposed a scoping review protocol that uses knowledge graphs and semantic reasoning for automated identification of IoMT vulnerabilities in remote patient monitoring (32).

Security by Design: The key principle is that security must be embedded in system architecture from the outset, not added as an afterthought (26, 32).

Security Threats and Solutions: Aruna et al. provided a comprehensive analysis of security and privacy challenges in healthcare IoT, identifying common attack vectors and proposed countermeasures (31). Kapoor et al. proposed energy-efficient secure monitoring frameworks using optimized clustering and ciphertext policies for remote patient data protection (27).

Disease-Specific Applications

Cardiovascular Disease: Continuous ECG, heart rate, blood pressure, and SpO2 monitoring with the ability to detect arrhythmias and heart failure at an early stage (8, 18).

Diabetes: Continuous glucose monitoring (CGM) with intelligent alerts for hypoglycemia and hyperglycemia (8).

COVID-19: RPM systems played a central role in monitoring COVID-19 patients at home and reducing hospital admission burden (12, 25).

Elderly Care: Vital sign monitoring and fall detection for independently living older adults is among the most important applications (6, 16).

Chronic Respiratory Disease: Monitoring of asthma and COPD patients, particularly during the COVID-19 pandemic (12).

Patient Engagement and Empowerment

IoT-based Remote Monitoring Systems (IoT-RMS) have been shown to improve patient engagement through three main stages (33):

Enabling: Providing patients with access to their health data through mobile applications and web portals.

Engaging: Facilitating active participation in health management through real-time feedback and personalized recommendations.

Empowering: Enabling patients to take control of their health through self-management tools and shared decision-making.

Data Analytics and Big Data Challenges

The continuous monitoring capabilities of IoMT systems generate massive volumes of health data, creating significant big data challenges (34):

Data Volume: The sheer volume of continuous physiological data requires efficient storage and processing solutions.

Data Velocity: Real-time analysis requires high-speed processing capabilities, often necessitating edge computing approaches.

Data Variety: Integration of data from multiple sensor types and sources requires sophisticated data fusion techniques.

Data Veracity: Ensuring data quality and accuracy across diverse sensor platforms remains a significant challenge.

Big data analytics platforms integrating Apache Kafka for real-time streaming and Apache Spark for processing have been demonstrated to enable effective vital signs monitoring and anomaly detection (28).

Discussion

The findings of this review indicate that IoMT systems have moved well beyond the laboratory stage and are now deployed across a broad spectrum of chronic and acute conditions. The fundamental shift this technology enables is a transition from reactive care (responding after a clinical event occurs) to preventive care (early detection through continuous monitoring) (2, 5).

These findings are broadly consistent with, and extend, previous reviews. Al-Turjman et al., reviewing intelligence in the IoMT era, anticipated the migration of analytics toward the edge that our four-layer findings now document as standard practice (3). The COVID-19 telehealth synthesis by Monaghesh and Hajizadeh (12) identified remote monitoring of vital signs as one of the most frequently deployed telehealth modalities during the pandemic, which our findings corroborate from the technical literature. Compared with the broad review of IoT applications in healthcare by Li et al. (2), which described applications and benefits at a general level, the present review adds a structured account of clinical outcome evidence, security approaches, and implementation barriers, and it covers literature through March 2026. Finally, our outcome synthesis aligns with the conclusion of Tan et al. (16) that the clinical value of RPM is most visible in safety and utilization outcomes, while quality-of-life and economic benefits remain incompletely established.

The architecture findings also merit comparison. Tan et al. (16) emphasized heterogeneity of monitoring modalities as a barrier to comparing outcomes across studies; our findings suggest that this heterogeneity extends to the technical layer, where device diversity and protocol incompatibility impede integration with clinical information systems. This technical-clinical interaction - heterogeneous devices producing heterogeneous evidence - is a cross-cutting theme that, to our knowledge, prior single-dimension reviews have not jointly addressed.

Technological Advancement

The four-layer architecture observed in most reviewed systems provides a stable architectural pattern for technology-clinical integration (9, 10, 21). Edge computing plays a pivotal role in this transformation: by moving processing closer to the sensor layer, latency is dramatically reduced and more timely clinical action becomes possible (14). This is particularly critical in pacemaker and cardiac rhythm monitoring (18, 35).

Recent advances in AI-driven approaches, particularly transformer-based models, have significantly enhanced the analytical capabilities of IoMT systems. The TL-SAM framework achieves 98.62% accuracy in disease classification, representing a substantial improvement over traditional machine learning approaches; however, such results derive from technical evaluations on curated datasets and require prospective clinical validation before informing practice (24).

Clinical Evidence

The most consistent evidence is in the domain of patient safety. The systematic review by Tan et al., analyzing 29 studies across 16 countries, demonstrated that RPM systems significantly reduced serious adverse events (16). This is consistent with independent study findings reviewed here (19, 22).

Results for treatment adherence were generally positive but heterogeneous. Tan et al. (16) noted that while some studies showed significant adherence improvements, others found no meaningful difference from usual care. This heterogeneity likely reflects differences in intervention design, follow-up duration, and population characteristics.

Tan et al. (16) reported mixed quality-of-life findings: while RPM interventions improved patients' mobility and functional status, the impact on other quality-of-life measures, such as physical and mental health symptoms, remained inconclusive. Results remain inconsistent across studies, and longer-term trials are needed.

While IoMT may reduce costs through fewer readmissions and administrative task automation (15), sufficient economic evidence to definitively establish cost-effectiveness has yet to be generated (16). However, there is encouraging evidence of reduced healthcare utilization and improved resource allocation (16).

The economics of IoMT-RPM deserve more granular discussion. The available trials capture utilization outcomes such as admissions, readmissions, and length of stay, but rarely convert these into rigorous cost-effectiveness estimates, and none, to our knowledge, report value-of-information analyses to guide investment decisions under uncertainty (16). Because the economics of remote monitoring are highly context-specific - depending on reimbursement models, hospital bed costs, staffing structures, and geography - economic findings from high-income settings cannot be assumed to transfer to middle-income health systems. Future economic evaluations in settings such as Iran should therefore model local cost structures explicitly and consider the distributional consequences of RPM deployment across urban and rural populations.

Implementation Challenges

Interoperability: One of the most critical barriers to widespread IoMT deployment is the lack of unified data exchange standards. The diversity of devices, incompatible communication protocols, and difficulty connecting to hospital information systems (EHR/EMR) are the principal drivers of this challenge (2, 19, 29). Without standards such as HL7 FHIR, large-scale deployment will continue to face considerable friction (9, 14). For health systems such as Iran's, pragmatic first steps include mandating FHIR-based interfaces in device procurement and developing national e-health interoperability profiles (2).

Beyond standards adoption, the interoperability problem has an architectural dimension. Recent work illustrates two complementary responses: fog-driven eHealth architectures that place gateway intelligence between heterogeneous devices and backend systems (9), and ontology-

based frameworks that mediate semantic interoperability across layers (20). The practical lesson from both lines of work is that interoperability cannot be retrofitted at the application layer alone; it must be engineered across the sensing, network, and middleware layers concurrently.

Security and Privacy: Health data ranks among the most sensitive personal information, and IoMT devices are vulnerable to a range of cyberattacks (13, 15, 31). Solutions including end-to-end encryption, multi-factor authentication, and blockchain have been proposed (15, 26, 30). Bughio et al. (32) proposed knowledge graphs and semantic reasoning as tools for automated identification and management of IoMT vulnerabilities.

Clinical Integration: IoMT's success depends on genuine integration into care processes. Connecting to EHR/EMR systems, defining clear roles and responsibilities for alert response, and preventing alert fatigue are essential operational requirements (9, 19, 29).

Digital Divide: Older adults, residents of remote areas, and individuals with low digital literacy may not benefit equally from these systems. Simplified user interface design, active training programs, and sustained technical support for these groups are essential strategies for bridging the digital divide (16).

The digital divide also raises questions of equity and ethics that extend beyond usability. Continuous monitoring produces fine-grained behavioral and physiological data whose secondary use is not always anticipated by patients; sensor accuracy can differ across skin tones, body habitus, and age groups; and reimbursement for RPM services is uneven across insurers and regions. Unless these issues are addressed through inclusive design, transparent data governance, and equitable coverage policy, IoMT-RPM risks amplifying existing disparities rather than reducing them. Cost sensitivity of target users is likewise material: several low-cost architectures reviewed here were designed precisely to keep the per-patient hardware cost within reach of resource-constrained settings (18, 22).

Future Directions

Based on the evidence reviewed, several key areas require attention:

1. Long-term Studies: Extended randomized controlled trials with follow-up periods of 12+ months are needed to establish sustained clinical benefits and cost-effectiveness.
2. Standardization: Development and adoption of universal data exchange standards (HL7 FHIR, IEEE 11073) to ensure interoperability across diverse platforms.
3. AI Integration: Further development of interpretable AI models that can be validated clinically and integrated into decision support systems.
4. User-Centered Design: Enhanced focus on usability for vulnerable populations, including elderly patients and those with limited digital literacy.
5. Regulatory Frameworks: Development of comprehensive regulatory frameworks that balance innovation with patient safety and data protection.
6. Health Economic Analysis: Rigorous cost-effectiveness analyses comparing IoMT-RPM with standard care across different healthcare systems and populations.

Conclusion

This narrative review demonstrates that the Internet of Medical Things (IoMT) has rapidly matured into a multi-faceted tool for remote patient monitoring between 2018 and 2026. The most consistent evidence, drawn principally from large systematic reviews, concerns patient safety and reductions in adverse clinical events [16]; evidence for treatment adherence is positive but heterogeneous, quality-of-life outcomes remain mixed (16), and economic evidence for cost-effectiveness is not yet sufficient.

From a technical standpoint, addressing the interoperability gap through standards such as HL7 FHIR (9, 14) and investing in security by design using encryption, multi-factor authentication, and semantic technologies (32) are non-negotiable requirements. The integration of advanced AI approaches, including transformer-based models (24), offers significant potential for enhancing diagnostic accuracy and clinical decision-making.

From a clinical standpoint, sensors must be validated in target populations before entering clinical decision-making workflows (6, 18). Integration of IoMT outputs with EHR systems and the definition of alert response protocols are equally essential (9, 19).

From a policy standpoint, compliance with data protection regulations, user-centered design for vulnerable populations (16), and the conduct of long-term cost-effectiveness studies are prerequisites for sustainable deployment (16).

Realizing the full potential of IoMT requires the convergence of technological, clinical, policy, and educational efforts. Future research should focus on long-term randomized controlled trials, comprehensive health economic evaluations, and outcome assessments in diverse and underserved populations (16).

Limitations: This review has several limitations. First, as a narrative review it does not apply formal quality appraisal or risk-of-bias assessment to the included studies, and judgments about the relative strength of evidence rely on study design (prioritizing large systematic reviews of randomized and observational studies over single-arm technical evaluations) and on the consistency of findings across studies, rather than on a formal grading instrument. Second, the evidence base is heterogeneous: part of the clinical outcome evidence derives from broader RPM interventions rather than IoMT-specific systems, and this was addressed by explicit qualification rather than statistical pooling. Third, publication and language restrictions (English and Persian) may have omitted relevant work in other languages, and the rapid evolution of the field means that some technological findings may age quickly. Finally, several included studies are technical evaluations without clinical validation, which limits the certainty of the corresponding claims.

Declarations

Authors' contributions

Dr Ehteshami conceived and designed the study. Maedeh Esmailzadeh and Abolfazl Rezaei conducted the literature search and drafted the initial manuscript. Dr Ehteshami and Maedeh Esmailzadeh critically revised the manuscript for important intellectual content. All authors read and approved the final manuscript.

Funds

The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Ethics approval and consent for the company

Not applicable. (As this study is a literature review, formal ethical approval was not required).

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

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