

# Internet of things-enabled biomedical engineering: current applications, challenges, and emerging directions

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## ABSTRACT

The internet of medical things (IoMT) is a structured integrative review of the internet of things (IoT) that focuses on the medical field, specifically on the integration of physiological sensors, medical devices, communication networks, and the clinical information systems to monitor and track patients' health and conditions continuously, and use data to support medical treatment. Through July 2026, a reproducible search and evidence audit of PubMed/MEDLINE, IEEE Xplore, Google Scholar, publisher/digital object identifier (DOI) records, and authoritative regulatory and standards repositories was conducted. The final evidence base consisted of 65 distinct sources that were assessed using a set of explicit eligibility criteria and evidence weighting. Wearable atrial-fibrillation screening, remote monitoring, digital inhalers and continuous glucose monitoring (CGM), and connected hospital infrastructure were shown to be clinically significant in large-scale studies, but such benefits were only seen if there was confirmatory pathway, workflow integration, data quality and persistent engagement. Cybersecurity, privacy, interoperability, validation, workforce capacity, equity, and lifecycle sustainability were all key challenges. The review also brought a synthesis and readiness framework that connects edge artificial intelligence (AI), federated learning, digital twins, advanced connectivity, and circular lifecycle management with measurable validation and governance requirements across the domains.

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## 1. INTRODUCTION

The internet of medical things (IoMT) is the biomedical application of connected sensing, embedded computing, communication, and health-information exchange. It includes wearable and implantable sensors, home-monitoring devices, connected therapeutics, gateways, edge and cloud platforms, and interfaces with clinical information systems. A clinically useful IoMT system is therefore not a single device; it is a socio-technical chain in which signal quality, secure transmission, semantic interpretation, algorithmic processing, clinical review, and action must remain reliable across the technology lifecycle [1]–[4].

IoMT can shift care from episodic observation toward continuous and contextualized monitoring. Remote patient monitoring (RPM), virtual wards, rhythm surveillance, connected inhalers, continuous glucose monitoring (CGM), and remotely managed cardiovascular implantable electronic devices (CIEDs) can extend care beyond the clinic and support earlier escalation [5], [6]. However, the same connectivity

enlarges the attack surface, increases the volume and sensitivity of longitudinal data, creates heterogeneous device-to-record interfaces, and may generate unmanageable alert burdens when responsibilities and workflows are not explicitly designed [7]–[10].

Figure 1 provides a conceptual view of the IoMT. The IoMT ecosystem includes wearable and implantable devices, home based monitoring systems, and smart-hospital infrastructure interconnected via cloud and edge computing, enabling continuous collection, transmission, and management of health-related data. This structure also accommodates hospital IoT, where connected device fleets, real-time location systems (RTLS), and interoperable data services must operate within institutional governance and patient-safety processes.

The aim of this review is threefold: i) to systematically assess current applications of IoMT and the strength of the evidence supporting them, ii) to identify: technical, clinical, organizational, regulatory, and equity barriers to safe scale-up of IoMT, and iii) to propose a trust-by-design framework that maps application domains to lifecycle requirements. The analysis is not about whether a sensor or algorithm can work in a controlled environment but whether it will work in a real-world environment in order to be clinically reliable after being deployed. Typically, the field is categorized in prior IoMT reviews based on either functional layers (sensing, communication, cloud, and analytics) or clinical application. This separation can create confusion about how a design decision impacts on clinical risk, staffing needs, information management, or compliance needs. What is novel about this review, is its cross-cutting synthesis: applications and representative outcomes are studied together, as well as the strength of the evidence, deployment barriers, and controls needed from design through deployment, monitoring and updating, and finally at the time of retirement.

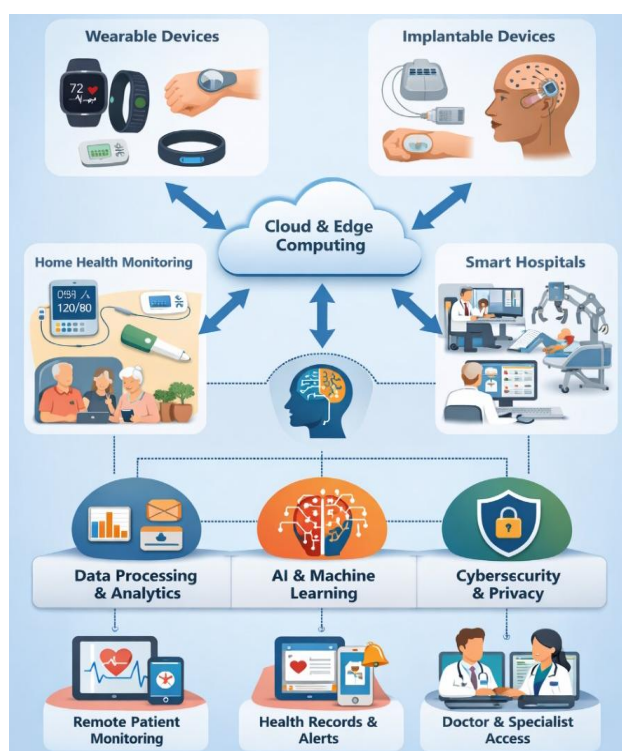


Figure 1. Conceptual overview of the IoMT

## 2. METHOD

Instead of a systematic review that complies with preferred reporting items for systematic reviews and meta-analyses (PRISMA), this study used an organized integrative review design. While maintaining an auditable connection between each referenced source and the claim it supports, the approach is suitable for combining diverse clinical studies, engineering validation reports, implementation evidence, standards, and regulatory guidelines. The cited source served as the unit of synthesis and could be an authoritative regulatory or technical standard, a systematic/scoping review, an expert consensus statement, or a peer-reviewed clinical or engineering study.

### 2.1. Review design and eligibility criteria

Sources were eligible when they: i) addressed a biomedical or healthcare use of a connected sensor, device, therapeutic, platform, or hospital system; ii) described device integration, data flow, clinical workflow, implementation, validation, security, privacy, interoperability, or governance; iii) were peer reviewed, or were official guidance or standards from bodies such as World Health Organization (WHO), Food and Drug Administration (FDA), National Institute of Standards and Technology (NIST), International Medical Device Regulators Forum (IMDRF), Medical Device Coordination Group (MDCG), International Electrotechnical Commission (IEC), International Organization for Standardization (ISO), or Institute of Electrical and Electronics Engineers (IEEE); iv) were available in English; and v) were published or current through 31 December 2025. Generic smart-city or non-health IoT studies, purely conceptual claims without a healthcare deployment context, duplicate records, and sources that did not support the statement for which they were cited were excluded.

### 2.2. Information sources and reproducible search strategy

To improve the reproducibility with the least impact on the review as PRISMA compliant, a second search was conducted in the revision stage using PubMed/MEDLINE and IEEE Xplore as main bibliographic databases. Citation chaining and additional discovery was performed using Google Scholar, verification of article metadata from publisher pages and digital object identifier (DOIs)/crossref records, and official WHO, FDA, NIST, IMDRF, European Commission/MDCG, IEC, ISO/IEEE, and HL7 repositories were used for standards and regulatory guidance. Records published between 1 January 2015 and 31 July 2026, and foundational standards or landmark evidence that were directly relevant to a claim were retained in the supplementary search; all other records were deleted. All other records were deleted from the search, while foundational standards or landmark evidence that were directly relevant to a claim were retained. Two main families of Boolean queries were used, with the database-specific syntax adapted accordingly: i) ("Internet of Medical Things" OR IoMT OR "medical IoT" OR "healthcare IoT") AND ("remote patient monitoring" OR wearable\* OR "atrial fibrillation" OR "digital inhaler" OR "continuous glucose monitoring" OR CIED OR "smart hospital" OR RTLS); ii) ("Internet of Medical Things" OR IoMT OR "connected medical device\*") AND (cybersecurity OR privacy OR interoperability OR FHIR OR "ISO/IEEE 11073" OR validation OR SaMD OR "edge AI" OR "federated learning" OR "digital twin\*" OR sustainability OR circular). Key reviews, consensus statements, and landmark studies were identified through a backward-chaining approach for evidence that was directly relevant.

Retrospective hit counts were not reconstructed as the original submission did not preserve the database-level hit counts. The strategy outlined above includes documentation of sources, search concepts, window of coverage, and verification process during the revision process, but the manuscript intentionally excludes a PRISMA flow diagram and does not claim to have captured the database comprehensively.

### 2.3. Screening process and reference audit

A total of 65 records from the submitted bibliography were found. Five exact duplicate records were found during a title, DOI, scope, and citation to claim audit and sixteen records were off-scope or misaligned with the associated claim. The data sources outlined in subsection 2.2 were used to specifically verify these 21 records, and they were replaced as a result of that verification. The revised synthesis then includes 65 unique sources: 44 are retained and 21 verified changes. The replacement was accepted only upon verification by exact title/DOI and/or direct claim to source and preference for the highest level of evidence type available (authoritative standard/guidance, systematic evidence, large prospective/pragmatic evidence, and smaller implementation evidence). Unsupported quantitative claims were not kept but instead eliminated or modified due to a weak substitute source.

The original submission did not create an exclusion log of every record so representative exclusion examples are reported on a category basis. These included: duplicate records being cited in alternate ways; papers about smart cities or industrial-IoT devices but absent a biomedical deployment context; network/blockchain simulations with no clinical or medical-device validation; artificial intelligence/explainable artificial intelligence (AI/XAI) papers without a healthcare IoMT context; and papers cited for their quantitative or regulatory claim but absent from their abstract or full text. Specific titles that are excluded are not rebuilt as that would result in an unverifiable screening history.

### 2.4. Data extraction and thematic coding

For each source, the following fields were extracted where applicable: application domain; device or data stream; study design and sample scale; reported clinical or operational outcome; architecture or integration requirement; cybersecurity and privacy concern; interoperability or provenance requirement; validation and lifecycle issue; workflow or human-factor dependency; equity consideration; and regulatory

relevance. Coding combined three a priori dimensions - application, architecture/data flow, and trust/safety-with inductive subthemes that recurred across the evidence. Category assignments were checked against the extracted evidence, and ambiguous items were resolved during synthesis by returning to the source and selecting the most conservative interpretation.

## 2.5. Evidence weighting and synthesis

Given the heterogeneity of the outcome, device, population and deployment models, evidence was weighted qualitatively, not pooled. Tier 1 included authoritative standards/regulatory guidance when the question was about requirements, systematic reviews/meta-analyses when it was about evidence synthesis, and randomized trials as well as large pragmatic digital studies when it was about the clinical or operational outcomes. Tier 2 included prospective device/algorithm validation studies, multicenter observational studies, and expert opinion with direct operational relevance. Tier 3 included single-center pilots, retrospective implementation reports and technical demonstrations. A "landmark trial" was different from a prospective validation study, in that it involved the basis of the study (large pragmatic or interventional setting) and the primary contribution to the study (establish clinical feasibility, diagnostic yield, or comparative effectiveness). Evidence tier was thus assigned based on design, purpose, scale, and relevance to the claim, not size of samples. Large trials were performed to measure clinical yield/effectiveness, and smaller pilots were performed primarily for the purpose of identifying workflow, usability, and implementation issues.

## 3. CURRENT APPLICATIONS

RPM is a broad service model in which physiologic measurements are transmitted to a care team for longitudinal review and escalation. Its clinical effect depends on the full pathway: appropriate patient selection, reliable sensing, data transmission, threshold design, alert ownership, confirmatory assessment, and a documented response. Cardiovascular rhythm monitoring provides the clearest scale evidence [4], [11], [12]. In the Apple Heart Study, 419,297 participants were enrolled; 0.52% received an irregular-pulse notification, atrial fibrillation (AF) was identified in 34% of analyzable electrocardiogram (ECG) patches, and the positive predictive value (PPV) of a notification accompanied by a subsequent tachogram was 0.84 [13]–[16]. In the Fitbit Heart Study, 455,699 participants were enrolled; 1.0% received an irregular-rhythm notification, AF was present in 32.2% of returned analyzable patches, and the PPV for concurrent AF was 98.2% [17], [18]. The randomized mhealth screening to prevent strokes (mSToPS) program further showed that immediate self-applied patch monitoring detected new AF in 3.9% of participants versus 0.9% with delayed monitoring at four months [19]–[22]. These findings support scalable case finding, but they also demonstrate why consumer alerts require signal-quality controls, confirmatory ECG testing, and defined clinical follow-up. Figure 2 demonstrates IoMT-enabled cardiovascular rhythm monitoring and AF screening workflow.

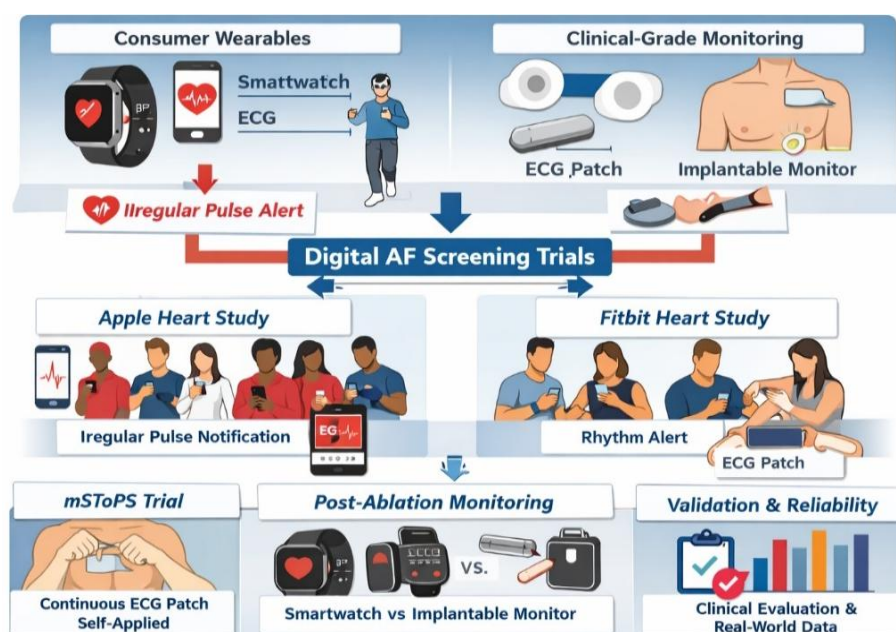


Figure 2. IoMT-enabled cardiovascular rhythm monitoring and AF screening workflow

Remote CIED management is a more regulated IoMT model because implanted devices generate scheduled transmissions and actionable alerts within specialist clinics. International consensus recommends early activation, maintenance of connectivity, risk-based alert programming, clear triage responsibilities, and sufficient staffing as transmission volume grows [23]–[25]. Evidence from operational programs shows that remote monitoring can reduce routine in-person follow-up and improve responsiveness, but benefits are constrained when alerts are not integrated into electronic records, when responsibilities are fragmented, or when patients lose connectivity [26].

Connected inhalers convert medication use and, in some systems, inhalation technique into time-stamped data that can support adherence assessment and targeted feedback. In the 24-week connected electronic inhalers asthma control trial 2 (CONNECT2) randomized study, the maintenance-and-reliever Digihaler intervention had an 88.7% probability of improving asthma-control odds compared with standard care, with a mean odds ratio (OR) of 1.35; reliever use decreased by 38.2% over the study period [27]–[29]. Systematic reviews indicate that digital inhalers can improve adherence or control-related outcomes in selected populations, while sustained engagement, device burden, clinician response, and patient selection remain decisive [30]–[32]. Thus, the value arises from a closed feedback loop rather than passive logging alone. CGM represents a mature connected-sensing platform because glucose time series can be shared with patients, educators, and clinicians through mobile and cloud services. In a randomized trial of adults with non-insulin-treated type 2 diabetes, CGM combined with remote telemonitoring and virtual educator visits produced a larger adjusted reduction in glycated hemoglobin than enhanced usual care and increased the probability of achieving a clinically meaningful reduction [33], [34]. Related work shows that patient-reported benefit depends on education, interpretation, and continued engagement [35]. Reviews emphasize that access, digital literacy, reimbursement, data governance, and continuity of follow-up determine whether CGM-enabled virtual care remains effective outside a trial [34], [36]–[38].

Hospital IoT includes RTLS, connected device fleets, smart beds and monitors, and middleware that transfers device observations into analytics or electronic health records. RTLS can reduce equipment-search time and improve visibility of high-mobility assets, but empirical benefits depend on location accuracy, staff adoption, maintenance, and governance of the resulting operational data [39], [40]. At the data layer, Health Level Seven International (HL7) Fast Healthcare Interoperability Resources (FHIR) supports modern application programming interface (API) exchange, while ISO/IEEE 11073 defines device-oriented models and communication profiles [41], [42]. Neither standard eliminates semantic work: implementations still require consistent identifiers, units, timestamps, calibration context, uncertainty, and provenance so that data remain interpretable and auditable across vendors and sites. Table 1 (see in Appendix) clarify current applications of IoMT, including RPM, wearable/patch-based AF detection, CIED remote monitoring, digital inhalers, CGM-enabled diabetes care, and in-hospital IoT systems.

Table 2 compiles sample outcome indicators from the key research mentioned above to improve cross-application quantitative synthesis. Because outcomes and populations vary significantly among application areas, the table is descriptive rather than meta-analytic.

Table 2. Comparative quantitative results from representative IoMT research

| Study/application             | Design/sample                                    | Primary metric(s)                                          | Representative result                                                                                                                 | Interpretive use                                                             |
|-------------------------------|--------------------------------------------------|------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------|
| Apple Heart Study [16]        | Prospective, n=419,297                           | Alert rate; AF confirmation; PPV                           | 0.52% notified; AF in 34% of analyzable ECG patches; PPV 0.84 for notification with subsequent tachogram                              | Population-scale feasibility; confirmation remains essential                 |
| Fitbit Heart Study [18]       | Prospective, n=455,699                           | Alert rate; AF confirmation; PPV                           | 1.0% notified; AF in 32.2% of returned analyzable patches; PPV 98.2% for concurrent AF                                                | High PPV under protocol-defined concurrent confirmation                      |
| mSToPS [20]                   | Randomized immediate vs delayed patch monitoring | New AF detection at 4 months                               | 3.9% immediate monitoring vs 0.9% delayed monitoring                                                                                  | Demonstrates increased diagnostic yield from active screening                |
| CONNECT2 digital inhaler [27] | 24-week randomized controlled trial (RCT), n=391 | Asthma-control odds; adherence; reliever use               | OR 1.35; 88.7% posterior probability of improved control; adherence 79.2% month 1 and 68.6% month 6; reliever use –38.2%              | Clinical benefit depends on engagement and feedback                          |
| CGM+telemonitoring [33]       | Randomized trial, n=105; 86 follow-up            | HbA1c change; relative risk (RR) of $\geq 0.5\%$ reduction | HbA1c –0.69% vs –0.33%; adjusted 0.65% greater reduction (95% confidence interval (CI) 0.17–1.12); RR 1.92 for $\geq 0.5\%$ reduction | Connected sensing is most effective when paired with educator-supported care |

#### 4. KEY CHALLENGES

Cybersecurity and privacy are patient-safety requirements in IoMT because compromised confidentiality, integrity, or availability may expose sensitive data, alter clinical information, interrupt monitoring, or affect therapy. Heterogeneous devices, long support periods, third-party components, and remote connectivity enlarge the attack surface. Security therefore begins with threat modelling, unique identity, least-privilege access, protected data, secure updating, logging, vulnerability disclosure, and recovery planning [9], [43]–[46]. National Institute of Standards and Technology Interagency or Internal Report (NISTIR) 8259A provides a baseline of device cybersecurity capabilities, while FDA guidance, MDCG 2019-16, and IEC 81001-5-1 apply a lifecycle perspective to medical-device and health-software security [43]–[46]. The practical implication is that a device cannot be considered secure because it passed a single premarket test; manufacturers and healthcare organizations need coordinated processes for software bills of materials, patching, monitoring, incident response, and communication throughout the supported life of the product.

Privacy governance is similarly architectural. Continuous IoMT streams can reveal sleep, activity, location, routines, treatment adherence, and social context beyond the immediate clinical measurement. General data protection regulation (GDPR) requirements and Health Insurance Portability and Accountability Act (HIPAA)-aligned safeguards, including the NIST SP 800-66 Rev. 2 implementation resource, shape consent, purpose limitation, data minimization, access, retention, audit, secondary use, and cross-organizational accountability [47], [48]. Privacy-preserving design should therefore determine which data are collected and where they are processed, rather than being added after the system architecture is fixed.

Interoperability remains a central barrier because IoMT systems differ in sampling rates, units, identifiers, metadata, proprietary formats, and implementation guides. FHIR can enable API-level exchange, but implementation variability and inconsistent semantic mapping limit portability and reuse [41]. Interoperability should be assessed at technical, syntactic, semantic, and organizational levels; a successful connection is not sufficient when the receiving system cannot interpret measurement context or assign responsibility for action.

ISO/IEEE 11073 supports standardized communication and data models for personal health devices, but real deployments still need gateways, terminology mapping, device identity, calibration status, uncertainty, and traceable provenance [42]. These requirements are especially important when data feed algorithms, longitudinal records, or digital twins, because an apparently minor loss of context can propagate into incorrect trends, alerts, or model predictions.

Regulatory and clinical validation become more complex when IoMT outputs drive diagnosis, prioritization, or therapy, or when analytics qualify as software as a medical device (SaMD). IMDRF principles require clinical association, analytical validation, and clinical performance [49]. Validation should also address subgroup performance, missingness, motion and contact artifacts, software updates, device-generation changes, and distribution shift. A model that performs well at release can become unsafe if its input population, sensor hardware, or workflow changes without monitoring.

The unit of clinical validation is often the entire socio-technical intervention. Changes in yield with wear time and confirmatory pathways [16], [18], [20], educator involvement and improvements in CGM benefits [33], [35], and alert governance and staffing and safety improvements with CIEDs [25], [26] all support the premise that yield changes with wear time and confirmatory pathways, educator involvement changes the benefits of CGM, and alert governance and staffing changes the safety of CIEDs. Technical issues can be translated into workload and safety risks because of energy limitations, poor connectivity, misalarms and data overload. COVID-era home oximetry and virtual wards also demonstrated key factors to safe deployment, including onboarding, patient selection, escalation protocols, and quality assurance [50], [51]. Table 3 highlights some of the most important challenges for IoMT, such as security and privacy constraints, interoperability barriers, regulatory and clinical validation requirements, and real world technological and operational limitations.

Thus, technical validation should be identified and planned for in an a priori manner both at device/network and clinical workflow levels. Authentication, authorization, encrypted transport, update integrity, vulnerability/penetration testing, incident recovery, and patchability should be recorded during security testing; FHIR/11073 conformance, terminology and unit consistency, timestamps, provenance, malformed or missing data, duplicate/out-of-order messages, and failover should be covered in interoperability testing; and discrimination, calibration, false-alert burden, subgroup performance, missingness, and post-update drift should be reported during clinical analytics. These tests translate the qualitative requirements listed in Table 3 into evidence of acceptance that is auditable, instead of being assumed to be synonymous with safe integration.

As a result, both the device/network and clinical process levels should have pre-specified technical validation. Clinical analytics should report discrimination and calibration along with false-alert burden, subgroup performance, missingness, and post-update drift; interoperability testing should cover FHIR/11073

conformance, terminology and unit consistency, timestamps, provenance, malformed or missing data, duplicate/out-of-order messages, and failover; and security testing should record authentication, authorization, encrypted transport, update integrity, vulnerability and penetration testing, incident recovery, and patchability. Instead of presuming that successful connectivity equates to safe integration, these tests translate the qualitative requirements in Table 3 into auditable acceptance proof.

Table 3. Technical and governance challenges in IoMT, with representative standards, test cases, and validation metrics

| Key challenge area                                    | Key implications                                                                                                                                                                                                                                                                                                  | Representative standards                                                                                                                                                                                                                                                                                                                                                                                                                                      |
|-------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Security (cybersecurity)                              | IoMT increases the attack surface through heterogeneous devices, remote connectivity, long support periods, and supply-chain dependencies. Security must preserve confidentiality, integrity, availability, authentic device identity, and recoverability across the lifecycle.                                   | NISTIR 8259A [43], FDA cybersecurity guidance [44], MDCG 2019-16 Rev.1 [45], IEC 81001-5-1 [46]. Verification examples: authenticated device identity; least privilege; encrypted transport (e.g., transport layer security (TLS) 1.2/1.3 or equivalent); protected data at rest where feasible; signed/verified updates; software bill of materials (SBOM) review; vulnerability scanning; penetration testing; patch/recovery testing; audit-log integrity. |
| Privacy governance                                    | Continuous streams can reveal health status, location, routines, adherence, and social context. Privacy choices directly affect architecture, retention, secondary use, and cross-organizational accountability.                                                                                                  | GDPR [47] and NIST SP 800-66 Rev.2 [48]. Test evidence should cover data minimization, purpose/consent mapping, role-based access, retention/deletion, pseudonymization where applicable, access logging, breach-response procedures, and verification that downstream analytics receive only necessary fields.                                                                                                                                               |
| Interoperability                                      | Connectivity alone is insufficient when identifiers, units, timestamps, terminology, device context, calibration status, or provenance are lost across systems.                                                                                                                                                   | FHIR evidence [41] and ISO/IEEE 11073 [42]. Test cases: profile/resource conformance; terminology and unit binding; identifier consistency; timestamp/time-zone handling; provenance/device-version retention; round-trip encode/decode; missing/invalid field handling; duplicate/out-of-order message handling; downtime/recovery and gateway mapping.                                                                                                      |
| Regulatory+clinical validation (incl. SaMD analytics) | Validation must cover clinical association, analytical validity, clinical performance, subgroup robustness, distribution shift, and the effect of software/device updates on real-world performance.                                                                                                              | IMDRF SaMD principles [49] plus application evidence [16], [18], [20], [33]–[35]. Report sensitivity, specificity, PPV/negative predictive value (NPV), area under the receiver operating characteristic curve (AUROC) where appropriate, calibration, false-alert rate, missingness, subgroup metrics, reference-standard definition, CIs, and pre/post-update drift or revalidation results.                                                                |
| Technological+operational limitations                 | Tight energy budgets, intermittent connectivity, and motion/contact issues degrade signal quality; risk of false alarms/misclassification→safety/workload issues if alert governance is weak; rapid RPM expansion (e.g., COVID-era) showed safety depends on onboarding, selection, escalation protocols, and QA. | Surveys on real-world constraints and safety/workload risks [2], [3]; COVID-era RPM/virtual ward evidence stressing patient selection, onboarding, escalation protocols, workflow integration, and QA [50], [51].                                                                                                                                                                                                                                             |

## 5. EMERGING DIRECTIONS

By processing signals local to the device, edge AI can lower latency, bandwidth usage, and the need for raw data to be transmitted. However, clinical readiness extends beyond high average accuracy; models must have signal quality checks, calibrated uncertainty, user friendly explanations of model outputs, and drift monitoring between generations of devices, different skin and tissue types, clinical populations and operating conditions [7], [8], [14], [23], [49]. The edge models should be equipped with controlled mechanisms for updating and provide a clear fallback in case of lack of confidence or connectivity [52]. End-to-end inference latency relative to clinical response window, memory/compute load, energy/battery impact, signal quality rejection, discrimination and calibration, performance in noisy or missing inputs, rollback and fallback behavior are all metrics to consider for readiness. A practical approach for algorithm metrics to be coupled with a clinically interpretable reference pathway is to use a wearable rhythm study [14], [15], [23].

Federated learning can enable the development of a multi-institutional model without bringing all raw records together, while still addressing privacy and security concerns. Data may be non-identically distributed, clients may drop out of the system, poisoning may occur, responsibility for validation may be unclear, and this can affect both performance and accountability [53]–[55]. However, these factors, namely secure aggregation, threat modelling, auditable participation, quality assurance at sites and evaluation at both global and sub-group level under realistic data variability, are crucial for clinical deployment. Readiness claims should not only cite methodological studies and reviews, but rather refer to mature clinical deployments where the evidence shows either performance against local/centralized baselines or external-site

discrimination/calibration, communication rounds/bandwidth, client-dropout tolerance, non-independent and identically distributed (IID) data sensitivity, aggregation reproducibility, and poisoning and inference attacks on the model [53]–[55].

Digital twins combine longitudinal IoMT measurements with mechanistic or data-driven models to represent a patient, device, care pathway, or hospital system. Reviews identify opportunities in personalized prediction and operational planning, but readiness varies with data integration, model validity, provenance, and governance maturity [56]–[59]. Advanced connectivity, including 5G and edge-cloud orchestration, may support denser device environments and responsive telemedicine, yet greater connectivity also increases dependency and attack surface [60], [61]. These technologies should be evaluated as coupled architectures, not isolated features. Sustainability is an emerging engineering requirement. Short replacement cycles, batteries, accessories, firmware obsolescence, and unsupported devices can increase cost and electronic waste and can undermine continuity of care. A circular IoMT lifecycle should consider modularity, repairability, software-support periods, secure reuse, procurement standards, energy efficiency, recycling, and safe data erasure at retirement [62]–[66]. Sustainability must be balanced with infection prevention, safety, cybersecurity, and regulatory traceability rather than treated as a simple reuse objective. Figure 3 depicts emerging directions in the internet of IoMT. Table 4 operationalizes the emerging-direction discussion by separating evidence maturity from the measurements needed before clinical scale-up.

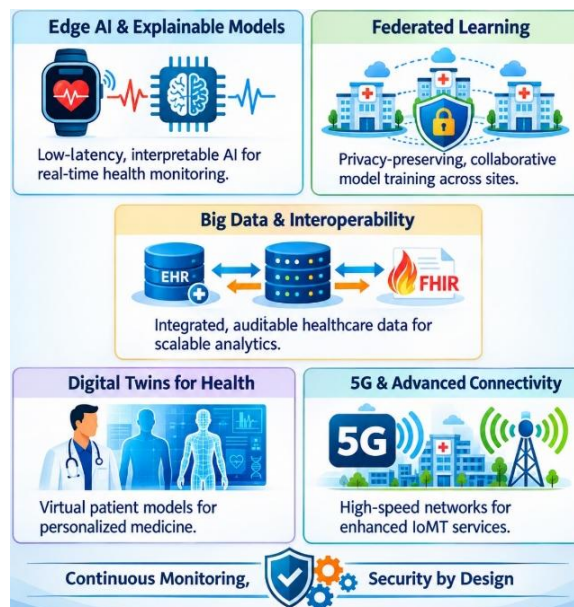


Figure 3. Emerging directions in the internet of IoMT

Table 4. Evidence maturity and readiness benchmarks for emerging IoMT directions

| Direction                     | Current evidence maturity in cited literature                                                                          | Readiness benchmarks before scale-up                                                                                                                         | Key deployment control                                                                  |
|-------------------------------|------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------|
| Edge AI                       | Wearable/device validation and prospective protocols; limited outcome-level deployment evidence [14], [15], [23], [52] | Latency; memory/compute; energy; sensitivity/specificity/AUROC as appropriate; calibration; artifact rejection; drift; rollback                              | On-device quality gate, controlled updates, and clinically safe fallback                |
| Federated learning            | Predominantly methodological/review evidence; cross-silo clinical deployment remains immature [53]–[55]                | Local vs centralized performance delta; external-site calibration; communication cost; dropout tolerance; non-IID robustness; poisoning/inference resistance | Secure aggregation, auditable participation, and site-level validation                  |
| Digital twins                 | Proof-of-concept and review-level healthcare evidence with variable clinical maturity [56]–[59]                        | Prediction error/calibration; temporal/external validation; data completeness; uncertainty; update latency; provenance; decision impact                      | Validated model scope, traceable data/model versions, and human oversight               |
| 5G/edge–cloud connectivity    | Enabling-technology evidence; benefit depends on use case and infrastructure [60], [61]                                | End-to-end latency; availability; packet loss; handover; coverage; failover under congestion/outage                                                          | Quality of service (QoS) monitoring, redundancy, and graceful degradation               |
| Circular lifecycle management | Emerging sustainability evidence and policy guidance [62]–[65]                                                         | Support-life duration; repairability; battery/energy burden; reuse/recycling rate; secure erasure success; e-waste pathway                                   | Procurement criteria, secure retirement, infection-control, and regulatory traceability |

## 6. DISCUSSION

### 6.1. Cross-domain trade-offs

IoMT domains differ in the location of risk and in the maturity of their evidence. Consumer RPM and AF screening scale rapidly because devices are widely distributed, but low event prevalence and variable adherence increase the need for confirmatory pathways and careful communication of false-positive risk. CGM and digital inhalers produce clinically interpretable longitudinal data, yet effectiveness depends heavily on education, behavior, and sustained service engagement. CIED remote monitoring has clearer specialist governance and regulatory pathways, but it creates concentrated alert workload and strong dependency on connectivity. Hospital IoT can deliver broad operational value, although benefits are often local and difficult to transfer because infrastructure, identifiers, and workflows differ between institutions. Table 5 summarizes these trade-offs.

Table 5. Cross-domain comparison of scalability, validation, regulatory readiness, workflow, equity, and sustainability

| Dimension             | Consumer RPM/AF                                                                 | CGM and digital inhalers                                                   | CIED remote clinics                                                     | Hospital IoT/RTLS                                                                  |
|-----------------------|---------------------------------------------------------------------------------|----------------------------------------------------------------------------|-------------------------------------------------------------------------|------------------------------------------------------------------------------------|
| Scalability           | High device reach; low-prevalence screening can generate follow-up demand       | Scales with cloud services but needs education and sustained engagement    | Scales within specialist programs; alert volume grows with enrollment   | Institution-wide scale requires infrastructure, identifiers, and change management |
| Validation focus      | PPV, sensitivity, signal quality, wear time, and confirmatory pathway           | Measurement accuracy plus clinical/behavioral effect of feedback           | Alert performance, connectivity, time to review, and clinical action    | Location/data accuracy, workflow benefit, downtime, and integration safety         |
| Regulatory readiness  | Variable: wellness to SaMD depending on claims and action                       | Generally regulated device; software/decision support may add requirements | High regulatory maturity for implantable devices and remote management  | Mixed: medical-device, health-IT, cybersecurity, and institutional governance      |
| Main workflow risk    | Unowned alerts and false reassurance                                            | Data overload or surveillance without supportive coaching                  | Alert fatigue and insufficient specialist workforce                     | Workarounds, poor staff adoption, context loss, and infrastructure dependency      |
| Equity/sustainability | Device ownership, connectivity, language, accessibility, and replacement cycles | Coverage, literacy, consumable sensors, batteries, and waste               | Access to specialist services, vendor lock-in, and long support periods | Capital cost, maintenance skills, energy use, asset retirement, and e-waste        |

### 6.2. Socio-technical integration, workforce, and equity

The primary failure in all domains is that data delivery is considered a proxy for care delivery. To be effective the alert must have an accountable recipient, a suitable response time, access to supporting information and a documented escalation route. Workforce modelling should take into account the volume of alerts, review time, out-of-hours (OOH) coverage, technical support, and patient on-boarding. Human-factors evaluation should cover the following: usability, alarm fatigue, workarounds, accessibility, language, disability, digital literacy, and opt-out or use of non-digital options. If these safeguards are not in place, IoMT can either migrate work to the patients and clinicians or exacerbate disparities even if technical performance is good [11], [25], [38].

### 6.3. Policy, standards, and lifecycle implications

Policy should align procurement, data governance, clinical evaluation, cybersecurity, and post-market monitoring. For manufacturers, this translates to the security-by-design, straightforward update policies, clinically significant performance statements, and evidence in relevant populations. For health care organizations, it is asset inventories, integration testing, alert governance, incident response, and monitoring of local outcomes. For regulators and standards bodies, it involves harmonizing what they expect from interoperable data, adaptive algorithms, cybersecurity maintenance and real-world performance. Life cycle sustainability introduces support period, repair, energy utilization, reuse, recycle and secure retirement requirements [66]. In the proposed framework, therefore, trust is an ongoing property that is shared among manufacturers, providers, clinicians, patients and policy makers.

### 6.4. Limitations

Several limitations to this review are noted. First, it is not a “database-complete” systematic review according to the PRISMA approach, but an integrative review organized around transparent revision-stage evidence audit; it is not intended to be read as an inventory or to be used for pooled effect estimation. Second, it is based on published evidence and information that are available and accessible as of 31 July

2026; as a result, conclusions on rapidly evolving technology, software and guidance may change. Third, there are significantly different types of validation designs, outcome definitions, wear time, algorithm versions, and reference standards, which make it difficult to compare across devices and domains. Fourth, a lot of the big data and regulatory evidence comes from the US and Europe, which may have a regional bias and also limits certainty for settings with alternative access to digital, infrastructure, or financing, or a different regulatory environment. Lastly, publication bias and selective reporting can overestimate successful implementation, and long-term safety and maintenance burden, cost and equity, environmental effects go unreported. Furthermore, targeted replacement of 21 records can lead to selection bias, as verification searches can find and return the most indexed, most cited, English-language and/or major-regulatory sources. This way, the number of citations matched to the claims is increased, which sometimes causes the breadth to be less and sometimes causes less of the negative findings to be cited, regional implementation reports, and less-indexed evidence to be cited. Where possible, replacement records have been matched to the same claim domain and highest applicable evidence tier, but the final corpus should still be read as a structured integrative synthesis, not as a comprehensive evidence inventory.

## 7. CONCLUSION

IoMT enables continuous monitoring, connected therapeutics, remote device management, and smarter hospital operations, but connectivity alone does not create clinical value. The evidence presented here is evidence that trustworthy deployment is a function of well-designed architecture, privacy governance, interoperable and provenance rich data, clinically appropriate validation, alert and escalation workflows, adequate workforce capacity, equitable access, and lifecycle sustainability. Researchers to report device versions, populations, missingness, local performance by subpopulations, workflow context, and longitudinal drift; clinicians and health systems to validate local pathways, set up ownership of alerts, track outcomes, and have fallback options; manufacturers of SaMD to ensure secure updates, interoperability, post-market evidence, and transparency of support-life, and policymakers to ensure alignment of cybersecurity, SaMD evaluation, standards, reimbursement, equity, and support-life. Only when these controls adapt to them are they promising in edge AI, privacy protecting distributed learning, digital twins, and advanced connectivity. The result is a roadmap, which is moving away from device-driven innovation, towards trust-by-design in IoMT systems, scalable, clinically useful, safe, and equitable.

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This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

| Name of Author  | C | M | So | Va | Fo | I | R | D | O | E | Vi | Su | P | Fu |
|-----------------|---|---|----|----|----|---|---|---|---|---|----|----|---|----|
| Hamza Abu Owida | ✓ | ✓ | ✓  | ✓  | ✓  | ✓ | ✓ | ✓ | ✓ | ✓ | ✓  | ✓  | ✓ | ✓  |
| Areen Arabiat   |   | ✓ |    | ✓  | ✓  | ✓ |   |   | ✓ | ✓ | ✓  |    |   |    |

C : **C**onceptualization

M : **M**ethodology

So : **S**oftware

Va : **V**alidation

Fo : **F**ormal analysis

I : **I**nvestigation

R : **R**esources

D : **D**ata Curation

O : Writing - **O**riginal Draft

E : Writing - Review & **E**ding

Vi : **V**isualization

Su : **S**upervision

P : **P**roject administration

Fu : **F**unding acquisition

## CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

## DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article

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## APPENDIX

Table 1. Overview of established and emerging IoMT use cases, their data streams, clinical value, and implementation considerations

| Application area                                     | What it is (IoMT use)                                                                                                                                | Common connected devices/data                                                                  | Key evidence/examples mentioned                                                                                                                                                                                                                                  | Main value/impact                                                                                                             | Key implementation notes/challenges                                                                                                                                 |
|------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| RPM                                                  | Connected devices continuously/periodically collect physiologic data and send it to clinician dashboards/triage systems for longitudinal management. | Heart rhythm, SpO <sub>2</sub> , BP, activity, glucose (wearables, patches, and home sensors). | Reviews describe RPM as a major IoMT driver; works best with safe escalation workflows.                                                                                                                                                                          | Proactive care, fewer in-person monitoring visits, earlier intervention.                                                      | Needs clear escalation pathways, safe data handling, efficient workflows for incoming data.                                                                         |
| Cardiovascular monitoring (Wearables/patches for AF) | Rhythm screening/surveillance using consumer wearables and clinical-grade patches; focus on AF detection.                                            | PPG signals, smartwatch ECG, continuous ECG patches.                                           | Apple Heart Study (irregular pulse→ECG confirmation); Fitbit Heart Study (wearable detection→ECG patch); mSToPS trial (ECG patch program increased new AF diagnoses); post-ablation/post-procedure smartwatch follow-up studies; ongoing validation comparisons. | Scalable AF screening and follow-up; can increase diagnostic yield when structured as a program.                              | Requires rigorous clinical validation; performance varies by device/algorithm and user behavior (wear time and adherence).                                          |
| Remote monitoring of CIEDs                           | Telemetry/alerts from implanted cardiac devices integrated into remote device clinics.                                                               | CIED transmission, connectivity/alerts into monitoring platforms.                              | Heart Rhythm Society+partners’ expert consensus guidance; real-world health system analyses.                                                                                                                                                                     | Improved responsiveness, fewer routine in-clinic follow-ups.                                                                  | Program design is critical: early activation, connectivity maintenance, governance of alert burden, staffing/workforce planning, interoperability with hospital IT. |
| Respiratory care (digital inhalers)                  | Connected inhalers capture medication use (and sometimes technique) enabling adherence monitoring and feedback loops.                                | Actuation events; sometimes inhalation parameters/technique.                                   | CONNECT2 RCT (maintenance-and-reliever digihaler in uncontrolled asthma improved control probability and interactions); systematic reviews/meta-analyses suggest benefit in some populations; respiratory society discussions on future strategies.              | Objective adherence measurement, targeted feedback, improved asthma control for some groups.                                  | Key questions: who benefits most, when to introduce devices, how to operationalize telemetry; usability and sustained engagement are major constraints.             |
| Diabetes care (CGM+remote review)                    | CGM streams data to apps/cloud for remote clinician review, virtual visits, and coaching pathways.                                                   | CGM glucose time series; data sharing to care teams/educators.                                 | RCTs with CGM+telemonitoring-enabled virtual educator visits (T2D not on insulin); studies on patient-reported outcomes; real-world RPM using CGM in high-need settings; reviews emphasize workflow/equity/governance.                                           | Supports remote diabetes management, behavioral support, and improved patient experience when paired with education/coaching. | Must match technology to workflow; equity/access, data governance, continuity, and follow-up determine durability of benefit.                                       |

Table 1. Overview of established and emerging IoMT use cases, their data streams, clinical value, and implementation considerations (*continued*)

| Application area                               | What it is (IoMT use)                                                                              | Common connected devices/data                                          | Key evidence/examples mentioned                                                                                                                                                                 | Main value/impact                                                                                                   | Key implementation notes/challenges                                                                                                                                                          |
|------------------------------------------------|----------------------------------------------------------------------------------------------------|------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| In-hospital IoMT infrastructure and data layer | Smart hospital systems connect devices for operational efficiency and interoperable data exchange. | RTLS/asset tracking; device fleet visibility; device data integration. | RTLS and asset tracking studies (reduce search time, improve utilization); 2024 scoping review on FHIR use in chronic disease ecosystems; ISO/IEEE 11073 standards for device interoperability. | Better equipment utilization and operational performance; improved data integration for analytics/decision support. | Interoperability is hard: variable FHIR implementations affect portability/semantic consistency; 11073 helps but often still needs gateways/mapping and careful context/provenance handling. |

## BIOGRAPHIES OF AUTHORS



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