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REVIEW ARTICLE

Multimodal Predictive Analytics for Early Disease Detection Using Wearable IoMT and Artificial Intelligence

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ABSTRACT

The convergence of wearable technology, Internet of Medical Things (IoMT), and artificial intelligence represents a paradigm shift in healthcare delivery from reactive treatment toward continuous, data-driven early disease detection. This review synthesizes recent evidence demonstrating how AI-powered wearable devices enable physiological monitoring and disease identification across cardiovascular, metabolic, neurological, and respiratory conditions with diagnostic accuracies exceeding 95% [1,2]. We examine architectural frameworks integrating edge computing and deep learning models, including convolutional neural networks and transformers. While substantial progress has been achieved, persistent challenges remain, including energy constraints, data interoperability, algorithmic bias, and privacy concerns under HIPAA and GDPR regulations. Emerging solutions through federated learning, explainable AI, and 6G connectivity offer pathways toward fully integrated wearable systems. This review provides evidence-based insights for advancing personalized, preventive healthcare through intelligent wearable technologies.

Keywords: Wearable devices, Internet of Medical Things, artificial intelligence, early disease detection, predictive analytics, personalized medicine

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INTRODUCTION

The healthcare system worldwide faces mounting pressure from aging populations and rising chronic disease prevalence, with late-stage disease management consuming approximately 80% of healthcare expenditures while preventive care receives only 3% of spending. Traditional episodic clinical care models often miss critical intervention windows, as patients typically present to healthcare providers only after symptoms manifest. The integration of wearable technology with the Internet of Medical Things and artificial intelligence represents a fundamental shift toward continuous, data-driven health monitoring, enabling disease detection during pre-symptomatic or early symptomatic phases [1,4].

Wearable IoMT devices have evolved dramatically from basic step counters to sophisticated medical-grade sensors capturing diverse physiological parameters, including electrocardiograms, photoplethysmography, skin temperature, respiratory rate, and blood oxygen saturation. These devices generate massive continuous data streams that, when analyzed using machine learning algorithms, reveal subtle patterns indicative of emerging health conditions [1,6]. Recent clinical evidence demonstrates that smartwatch-based atrial fibrillation detection achieves sensitivities and specificities exceeding 95% when validated against simultaneous ECG recordings, with several algorithms receiving FDA clearance for clinical use [7,8].

The pandemic catalyzed rapid development of wearable-based infection detection systems, with large-scale studies demonstrating that physiological changes, including elevated resting heart rate, reduced heart rate variability, and altered

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respiratory patterns,, precede COVID-19 symptom onset by 1 to 7 days, achieving detection sensitivities of 93.8 to 99.2% [9,10]. These applications illustrate the transformative potential of continuous wearable monitoring for population-level health surveillance and individual patient benefit. Remote patient monitoring through wearables reduces hospital readmissions by 15-20% for chronic conditions while extending specialty care access to underserved rural populations.

This review examines the technological foundations, clinical applications, technical challenges, and future directions of AI-integrated wearable IoMT systems. We synthesize evidence from 2019 to 2025 regarding disease detection capabilities, architectural innovations, and regulatory considerations shaping this rapidly evolving field.

METHODOLOGY

Search Strategy and Data Sources

This narrative review synthesized literature on multimodal predictive analytics for early disease detection using wearable Internet of Medical Things (IoMT) devices and artificial intelligence published between January 2019 and August 2025. We conducted comprehensive searches across PubMed, PubMed Central, Google Scholar, Scopus, IEEE Xplore, and Web of Science databases. Search terms included combinations of: "wearable devices," "wearable sensors," "Internet of Medical Things," "IoMT," "artificial intelligence," "machine learning," "deep learning," "early disease detection," "predictive analytics," "atrial fibrillation detection," "continuous glucose monitoring," "smartwatch," "physiological monitoring," "health monitoring," "cardiac monitoring," "respiratory monitoring," "neurological disease detection," "Parkinson's disease," "fall risk," "seizure detection," "sleep apnea," "COVID-19 detection," "edge computing," "federated learning," "explainable AI," "algorithmic bias," and "digital health." Boolean operators (AND, OR) were used to combine terms systematically.

Inclusion and Exclusion Criteria

Sources were included if they: (1) addressed wearable IoMT systems or devices for health monitoring or disease detection; (2) incorporated artificial intelligence, machine learning, or deep learning methodologies; (3) were published between 2019-2025 to capture recent technological evolution and clinical validation; (4) were peer-reviewed empirical studies, systematic or narrative reviews, clinical validation studies, technical reports, or regulatory guidance; (5) were published in English; (6) demonstrated clinical application or translational potential; and (7) provided evidence regarding diagnostic accuracy, technical implementation, or clinical outcomes. We excluded: (1) purely theoretical papers without clinical application or empirical evidence; (2) opinion pieces or editorials lacking peer review; (3) conference abstracts without full-text availability; (4) studies focused exclusively on non-health-related wearable applications; and (5) publications without clear methodology or insufficient technical detail.

Selection Process and Data Extraction

Initial database searches yielded 312 potentially relevant records. After removing duplicates (n=84), two authors independently screened titles and abstracts, identifying 156 articles for full-text review. Following full-text assessment, 72 sources met the inclusion criteria and were retained for synthesis. Disagreements regarding inclusion were resolved through discussion and consensus. Data extraction focused on: (1) specific diseases or health conditions targeted; (2) wearable modality and sensor type; (3) AI/ML methodologies employed (CNN, LSTM, transformers, etc.); (4) reported diagnostic accuracy or performance metrics; (5) clinical validation status; (6) technical challenges addressed; (7) privacy and security approaches; and (8) regulatory considerations. Given the rapid technological evolution, wide scope spanning hardware, software, and clinical applications, and the need to integrate diverse perspectives from biomedical engineering, computer science, and clinical medicine, we adopted a narrative synthesis approach rather than a systematic review methodology (e.g., PRISMA), which is appropriate for comprehensively evaluating emergent technologies and translational research.

Quality Assessment

Quality evaluation prioritized: (1) clinical validation status (FDA clearance, peer-reviewed clinical trials preferred over early-stage research); (2) peer review in indexed journals or reputable conferences; (3) clarity of methodology and reproducibility; (4) sample sizes and statistical rigor where applicable; and (5) transparency regarding limitations. We categorized evidence by maturity level: foundational research, clinical translation, and FDA-cleared systems to reflect implementation readiness.

Evolution and Architecture of Wearable IoMT Systems

The trajectory of wearable health technology spans from rudimentary pedometers in the early 2000s to today's sophisticated biosensing platforms. The introduction of the Apple Watch in 2014 marked a watershed moment, incorporating optical heart rate sensors, accelerometers, gyroscopes, and eventually electrocardiogram capabilities within a wrist-worn form factor [5,11]. Medical-grade wearable patches emerged simultaneously, featuring multi-parameter biosensing in skin-interfaced, wireless configurations with flexibility enhancing patient comfort and signal quality [12,13].

Modern wearable IoMT systems comprise three interconnected computational tiers: on-device processing executing lightweight models directly on microcontrollers, edge computing nodes at local gateways performing intermediate-complexity tasks, and cloud infrastructure hosting resource-intensive analytics and longitudinal data analysis [6,14]. This distributed architecture balances competing demands for real-time responsiveness, computational capability, energy efficiency, and communication bandwidth.

The Internet of Medical Things ecosystem encompasses interconnected medical devices, sensors, and healthcare systems collecting, transmitting, and analyzing health data in

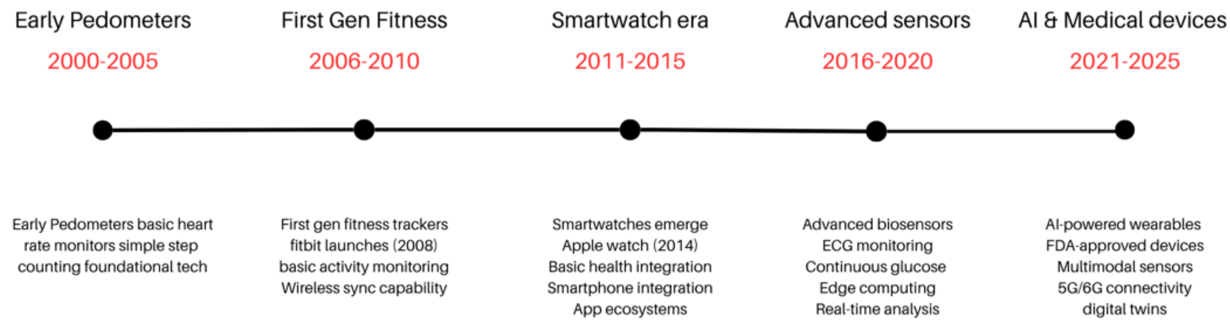

Fig. 1: Evolution Timeline of Wearable Technology & IoMT Integration: Historical evolution of wearable technology and IoMT integration in healthcare from 2000 to 2025, highlighting key technological milestones and innovations.

real-time. Security layers, including end-to-end encryption, blockchain-based audit trails, and multi-factor authentication, protect data confidentiality and integrity during transmission from wearables through communication networks to cloud storage [16,17,18].

Fast healthcare interoperability resources (FIHR) standards enable seamless data exchange between wearable systems, electronic health records, and clinical decision support tools, widespread implementation remains incomplete across wearable manufacturers [19,20]. FHIR defines modular data resources representing clinical concepts with standardized APIs facilitating integration of consumer devices into clinical workflows.

AI Techniques and Deep Learning Applications

Artificial Intelligence techniques applied to wearable health data progress from classical machine learning requiring manual feature engineering to deep learning automatically learning feature representations from raw sensor signals [5,11]. Convolutional neural networks excel at extracting spatial patterns from sensor data, identifying morphological features in physiological waveforms with particular utility for ECG and photoplethysmography analysis [22,23].

Long short-term memory networks address temporal dependency modeling inherent in physiological time-series data through gated mechanisms controlling information flow across extended sequences [24,25]. LSTM networks achieve glucose prediction accuracies within 5% error margins, the clinical standard, enabling preemptive interventions to prevent dangerous hypoglycemia episodes [26,27].

Transformer architectures employing self-attention mechanisms have recently demonstrated remarkable success in physiological signal analysis by computing relationships between all time points simultaneously, enabling parallel processing and efficient capture of long-range dependencies superior to sequential LSTM processing [28,29]. Multi-head attention mechanisms allow models to dynamically focus on the most relevant temporal context for each prediction, with multiple attention heads learning distinct patterns in data [30,31].

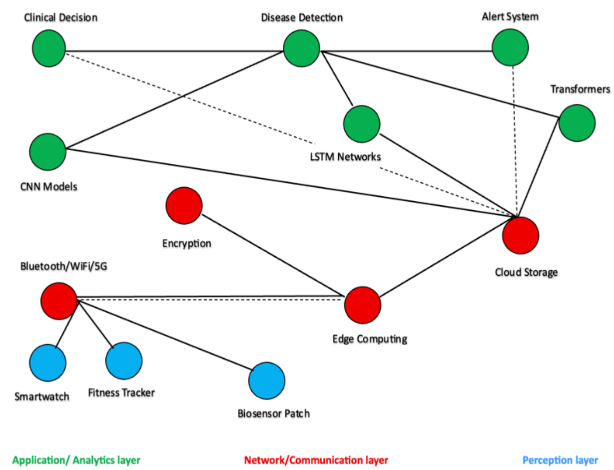

Fig. 2: IoMT Architecture for AI Health Monitoring: Architectural framework of AI-integrated IoMT system for wearable health monitoring showing the three-layered structure from sensor data acquisition to clinical decision support.

Recent transformer-based foundation models pretrained on large continuous glucose monitoring datasets demonstrate superior generalizability across diverse patient populations compared to patient-specific LSTM models. Attention mechanisms integrated into CNN-LSTM hybrid architectures improve interpretability by identifying temporal segments and spatial features contributing significantly to predictions, providing insights into physiological mechanisms underlying health conditions [33,34].

Clinical Applications and Disease Detection

Cardiovascular Disease Detection

Atrial fibrillation detection through smartwatch photoplethysmography exemplifies successful clinical translation of AI-powered monitoring, with algorithms achieving sensitivities and specificities exceeding 95% when validated against simultaneous ECG recording [7,35]. The Apple Heart Study, involving over 400,000 participants, demonstrated that PPG-based irregular pulse notification

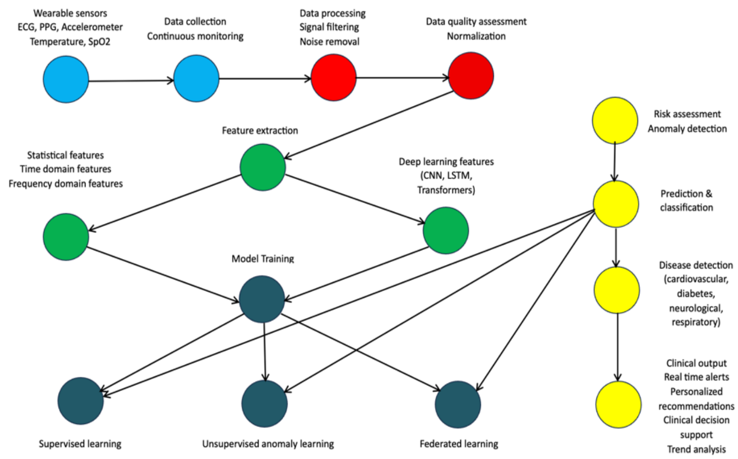

Fig. 3: AI/ML workflow for Wearable Disease Detection: AI-driven workflow for early disease detection using multimodal wearable sensor data, from data acquisition through preprocessing, feature extraction, model training, to clinical decision support

achieved a 34% positive predictive value for AF confirmed by subsequent ECG patch monitoring. Recent studies report accuracies approaching 99% with acceptable unclassifiable rates of 5 to 12% due to motion artifacts. [37,8].

Diabetes and Metabolic Monitoring

Continuous glucose monitoring combined with AI prediction algorithms has revolutionized diabetes management, with LSTM networks achieving prediction accuracies enabling preemptive interventions 30 to 60 minutes before dangerous glucose levels occur [26,27]. AI-enhanced CGM systems detect pre-diabetes and early Type 2 diabetes onset through subtle glucose dysregulation patterns invisible to traditional diagnostic criteria, enabling lifestyle interventions that reverse metabolic dysfunction before permanent pancreatic damage occurs [29,38].

Neurological Disease Detection

Wearable sensors paired with machine learning enable objective quantification of Parkinson's disease movement abnormalities, with deep learning classification of accelerometer and gyroscope data achieving 94to 95% accuracy in identifying pathological movements [39,40]. Fall risk prediction in elderly and neurologically impaired populations achieves area under the curve values of 0.86 when machine learning models process wrist-worn accelerometer data. Wireless EEG headbands combined with AI seizure detection algorithms provide comfortable monitoring during daily activities, with edge computing implementations enabling real-time seizure alerts while preserving privacy through local data processing rather than cloud transmission [42,43]. Wearable detection systems replicate polysomnography diagnostic capabilities for sleep apnea in home environments with 85-89% accuracy, with Apple and Samsung receiving FDA clearance for smartwatch-based sleep apnea detection [43,44].

Respiratory Disease Detection

The COVID-RED trial involving nearly 18,000 participants found that algorithms combining wearable physiological data with self-reported symptoms provided infection alerts a median of 7 days earlier than symptom-based algorithms alone, achieving 93.8to 99.2% sensitivity [9,45]. Respiratory rate monitoring through chest-worn or wrist-worn accelerometers detects breathing pattern abnormalities associated with pneumonia and chronic obstructive pulmonary disease, with novel respiratory biomarkers achieving ICU-grade accuracy for continuous pulmonary function assessment [10,46].

Data Management, Security, and Privacy

Data Infrastructure and Interoperability

IoMT data management encompasses complete lifecycle challenges from sensor signal acquisition through long-term archival storage, requiring robust infrastructure addressing volume, velocity, variety, and veracity inherent in wearable-generated data [6,14]. Short-range wireless protocols predominantly using Bluetooth Low Energy transmit data from wearables to local gateway devices aggregating multisensor streams before cloud transmission. Cloud storage architectures must accommodate both hot data requiring immediate access for real-time analytics and warm/cold historical data archived for longitudinal analysis.

FHIR integration enables seamless data exchange between wearables and electronic health records, through implementation requires compliance with both HIPAA and GDPR when health data crosses jurisdictional boundaries [19,47]. Recent initiatives demonstrate successful mapping of wearable data streams to FHIR resources, facilitating integration of consumer devices into clinical workflows.

Security, Privacy, and Ethical Considerations

Wearable IoMT systems face escalating cybersecurity threats, including insecure device firmware, unencrypted wireless communication, cloud storage breaches, and compromised algorithms producing manipulated health insights [48,49]. End-to-end encryption with AES 256-bit keys provides military-grade protection, while Transport Layer Security secures data in transit [18,50].

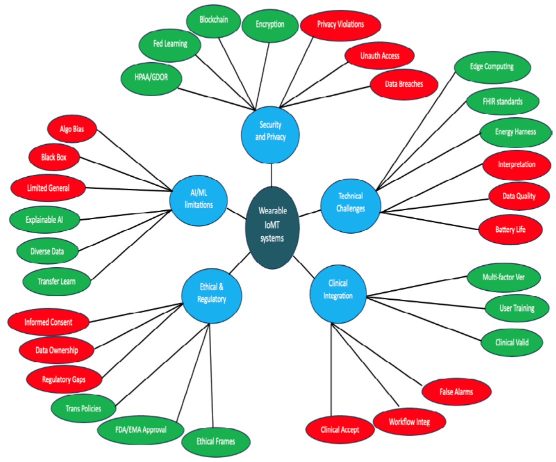

Fig.4: IoMT Challenges and Solutions: Major challenges and corresponding solutions in AI-powered wearable IoMT systems for healthcare, organized by technical, security, AI limitations, ethical, and clinical integration domains.

Blockchain technology offers a decentralized security architecture with distributed ledger systems storing encrypted health data across multiple nodes with tamper-proof audit trails recording all access events [16,17]. Differential privacy techniques inject statistical noise into datasets before analysis, preventing identification of individual records while preserving aggregate patterns useful for population health research [14,51].

Federated learning advances privacy protection by training machine learning models on distributed wearable data without centralizing raw sensor readings – only model parameters are update across devices, keeping personal data local [52,53]. The Health Insurance Portability and Accountability Act establishes privacy and security standards for protected health information, through consumer wearables used for personal wellness tracking often fall outside HIPAA's scope, creating regulatory gaps where data protection remains voluntary 48,50].

The European Union's General Data Protection Regulation provides more comprehensive coverage, applying to any organization processing personal data of EU residents regardless of healthcare context, mandating explicit user consent, purpose limitation, and data minimization [48,54].

Ethical challenges span informed consent, algorithmic transparency, data ownership, and equitable access [55,56]. Explainable AI techniques, including SHAP values and attention visualization, reveal which input features drive predictions, enabling clinicians to validate model reasoning [29,33]. Algorithmic bias threatens to perpetuate healthcare disparities if training datasets underrepresent certain demographic groups, with PPG-based heart rate monitoring demonstrating lower accuracy in individuals with darker skin pigmentation due to increased melanin absorption of optical signals [3,58,59].

Technical Challenges and Limitations

Power consumption represents a fundamental constraint limiting wearable functionality, with current smartwatches requiring daily charging while medical-grade patches typically last 7-14 days before battery replacement [59,60]. Energy harvesting technologies, including thermoelectric generators exploiting temperature gradients between skin and ambient air, achieve power densities of 3.5-12.3 $\mu W/cm^2$ sufficient for low-power sensors [59,12]. Triboelectric nanogenerators harvesting energy from body motion generate peak powers exceeding 900 μW from wrist-worn configurations, though harvested power remains insufficient for continuous multisensor operation with real-time AI processing.

Signal quality degradation from motion artifacts, sensor displacement, and environmental interference creates substantial challenges for wearable diagnostics [1,61]. PPG signals are particularly susceptible to motion artifacts during physical activity, with advanced signal processing techniques, including adaptive filtering and wavelet denoising, mitigating but not eliminating artifacts [8,37].

Model generalizability across diverse populations represents a persistent limitation where AI systems trained on homogeneous datasets fail when deployed to demographic groups underrepresented in training data [3,58]. Most wearable AI research utilized datasets from developed countries with predominantly younger, healthier, lighter-skinned participants, resulting in models underperforming for elderly, diseased, or racially diverse populations [57,58]. Transfer learning and domain adaptation techniques address generalizability by fine-tuning models pretrained on large source datasets using limited target population data [32,62].

Deep neural networks achieving the highest predictive performance lack transparency, making clinicians hesitant to trust automated recommendations without understanding the underlying reasoning [29,33]. Explainable AI methods improve interpretability but often reduce accuracy, creating tension between model accuracy and clinical interpretability [33,58].

Future Directions and Innovations

Emerging Technologies

Flexible hybrid electronics combining stretchable polymer substrates with functional silicon components create conformable devices maintaining intimate skin contact during movement [12,13]. Roll-to-roll manufacturing techniques enable high-volume, low-cost production of disposable wearable patches integrating multiple biosensors – ECG electrodes, temperature sensors, and sweat analysis, within ultrathin form factors [13,63].

Non-invasive sweat analysis detects biomarkers including cortisol, lactate, glucose, and electrolytes through electrochemical sensors integrated into skin patches or textile fabrics, extending wearable capabilities beyond traditional vital signs [13,63]. Ingestible capsules containing miniaturized sensors traverse the gastrointestinal tract, enabling diagnostic imaging and gut microbiome sampling while transmitting data wirelessly.

6G Networks and Distributed Computing

Sixth-generation wireless networks will enable terabit-per-second data rates, sub-millisecond latency, and connection densities supporting millions of devices per square kilometer, addressing current bottlenecks in real-time remote monitoring and high-resolution medical data transmission [64,65]. Network slicing technology allocates dedicated virtual networks for healthcare applications with guaranteed quality of service parameters, preventing interference from consumer traffic during medical emergencies [65,66].

Digital Twins and Personalized Medicine

Digital twin technology creates dynamic virtual patient models continuously updated with real-world data from wearables, electronic health records, genetic profiles, and medical imaging, simulating physiological processes, disease progression, and treatment responses [67,68]. Cardiovascular digital twins model electrical and mechanical heart function using patient-specific anatomy, predicting arrhythmia risk and optimal treatment settings [68,69]. Metabolic digital twins simulate glucose-insulin dynamics incorporating continuous glucose monitor data, meal composition, physical activity, and stress levels, providing personalized dietary recommendations and medication adjustments [67,70].

Multimodal Sensor Fusion

Multimodal sensor fusion combines information from multiple sensing modalities to achieve diagnostic accuracy exceeding individual sensor capabilities, leveraging complex interdependencies among physiological parameters that single-parameter monitoring misses [71,72]. Attention mechanisms learn optimal weighting of different modalities for specific tasks, with transformer architectures employing cross-modal attention discovering complementary information integration patterns [30,72].

Conclusions and Recommendations

Artificial intelligence – powered wearable IoMT systems have matured from research prototypes to clinically validated tools enabling early disease detection and continuous health monitoring. Substantial evidence confirms diagnostic capabilities approaching or exceeding traditional methods across cardiovascular conditions (atrial fibrillation >95% accuracy) [7,35], metabolic diseases (glucose prediction <5% error) [26,27], neurological disorders (Parkinson's detection 94% accuracy) [39,40], and respiratory infections (COVID-19 detection 93% sensitivity). These achievements span three technological domains: flexible biosensor hardware, edge-cloud hybrid computing architectures, and deep learning methodologies, including convolutional neural networks, LSTM networks, and transformers enabling automated feature learning from raw sensor signals [1,5,11].

Early disease detection through wearables enables interventions preventing irreversible damage: anticoagulation preventing strokes in atrial fibrillation patients, lifestyle modifications reversing pre-diabetes, and neuroprotective therapies slowing Parkinson's progression. Remote patient monitoring reduces hospital readmissions by 15 to 20% while extending specialty care access to underserved populations. Personalized medicine achieves practical implementation through digital twins optimizing therapy selection for individual patient physiology [67,68].

Critical challenges persist despite remarkable progress. Energy constraints, data quality issues from motion artifacts, interoperability gaps, algorithmic bias, security vulnerabilities, and privacy concerns demand continued research [1,6,48,58,59]. Researchers should prioritize diverse representative datasets addressing algorithmic bias and improving model generalizability, advance explainable AI maintaining high accuracy while providing interpretable rationales, and develop continual learning algorithms enabling personalization. Developers should implement privacy-by-design principles, adopt open standards including FHIR, conduct rigorous clinical validation, and optimize energy efficiency through edge AI inference and energy harvesting [15,19].

Policymakers should establish regulatory pathways for continuously learning AI systems, mandate interoperability standards preventing vendor lock-in, update privacy regulations addressing gaps in consumer wearable coverage, invest in digital health infrastructure enabling equitable technology access, and develop reimbursement policies compensating remote monitoring services. The convergence of wearable technology, IoMT infrastructure, and artificial intelligence promises a transformation of healthcare toward early detection, personalized intervention, and continuous health monitoring, fundamentally improving patient outcomes and global health equity when developed and deployed thoughtfully.

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CONFLICTS OF INTEREST

The authors of this study have no conflicts of interest.

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