

From data to action: Wearable AI for personalized proactive health

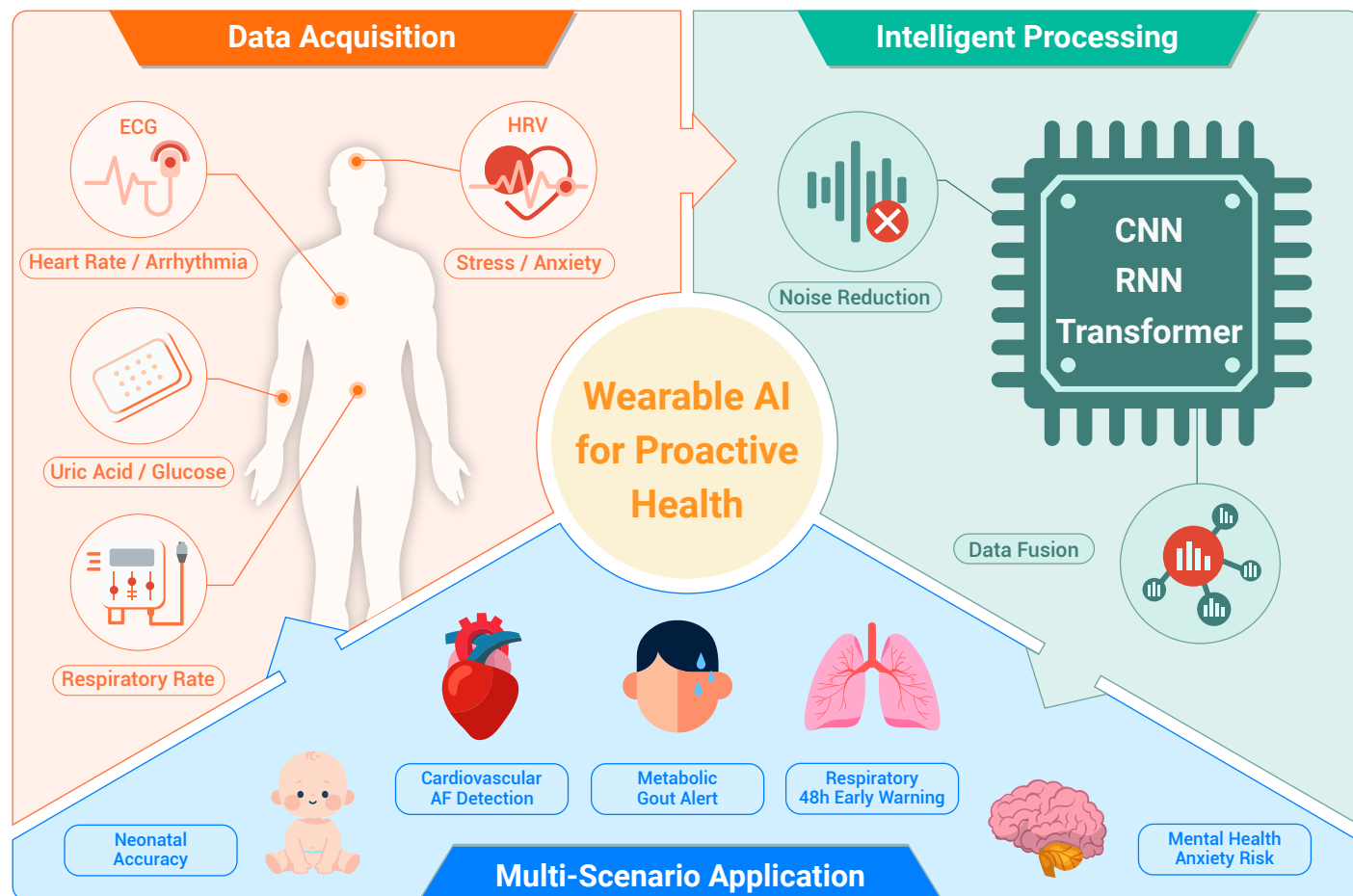
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Received: December 8, 2025; Accepted: March 19, 2026; Published Online: March 20, 2026; <https://doi.org/10.59717/j.xinn-med.2026.100209>

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GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- Wearable artificial intelligence (AI) devices enable real-time health monitoring for proactive care.
- Edge computing processes health data locally on AI devices to protect personal privacy.
- Multimodal fusion enhances the accuracy of health assessment and disease early warning.
- Wearable AI will deeply integrate into healthcare despite sensor and data standardization challenges.
- Wearable AI will offer accessible preventive care to reduce the social burden of chronic diseases.

From data to action: Wearable AI for personalized proactive health

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Received: December 8, 2025; Accepted: March 19, 2026; Published Online: March 20, 2026; <https://doi.org/10.59717/j.xinn-med.2026.100209>

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Citation: Liu G., Ma W., Zhang H., et al. (2026). From data to action: Wearable AI for personalized proactive health. *The Innovation Medicine* 4:100209.

With the advancement of AI and wearable devices, proactive health management has entered a new era. Wearable AI enables real-time physiological monitoring, early disease warning, personalized interventions and remote medical services, greatly enhancing the intelligence of health management. This review systematically summarizes its latest progress in cardiovascular health, metabolic disease diagnosis, respiratory/neonatal monitoring and mental health assessment, emphasizing AI's role in data processing and disease prediction with quantified clinical evidence. It also addresses technological challenges and future directions, providing a theoretical and practical basis for the intelligent application of proactive health management.

INTRODUCTION

Proactive health management has become increasingly pivotal in contemporary society, especially amid the rising prevalence of non-communicable diseases (NCDs) such as obesity, diabetes, and cardiovascular diseases. This surge in chronic conditions necessitates a fundamental shift from reactive healthcare—centered on post-illness treatment—to a proactive paradigm that prioritizes disease prevention and health promotion. Proactive health management empowers individuals to take charge of their well-being through informed lifestyle choices and continuous health monitoring, with robust evidence confirming that lifestyle modifications (e.g., enhanced physical activity, balanced nutrition, and regular screenings) significantly improve health outcomes and reduce healthcare costs across diverse populations.¹ Moreover, the integration of digital technologies into health management has emerged as a cornerstone in boosting health literacy and expanding access to health resources, fostering a culture of prevention.²

The evolution of wearable technology has been instrumental in transforming health monitoring and management. Wearable devices, ranging from fitness trackers to smartwatches, have gained widespread adoption due to their ability to deliver real-time data on key health metrics—including physical activity, heart rate, and sleep patterns. Beyond empowering individuals to self-monitor, these devices encourage healthier behaviors, while aggregated data offers valuable insights for public health initiatives and helps healthcare providers identify population health trends.³ However, fully unlocking their potential for health promotion and disease prevention remains a challenge. Current barriers include ensuring data accuracy, addressing privacy concerns, and enhancing user engagement to maximize the effectiveness of these tools in proactive health management.⁴

Artificial intelligence (AI) has emerged as a transformative force in health data analysis, particularly when integrated with wearable technology. Machine learning and deep learning algorithms enable the processing and interpretation of complex, multi-dimensional health data, delivering personalized insights and actionable recommendations. AI enhances wearable functionality through predictive analytics, identifying potential health risks and triggering timely interventions—for example, analyzing patterns in physical activity and vital signs to forecast adverse health events and inform proactive strategies.⁵ This synergy not only improves individual health outcomes but also supports broader public health efforts by uncovering population-level trends and risk factors. As AI technology advances, its role in health data analysis will become increasingly critical in shaping the future of proactive health management.⁶

The urgency of integrating wearable technology with AI for proactive health management cannot be overstated. As the global burden of NCDs grows, innovative strategies for health promotion and disease prevention are imperative. This integration offers a unique opportunity to build a comprehensive health management ecosystem: one that empowers individuals to take control of their health while equipping healthcare providers with tools for personalized care. This synergy not only enhances individual outcomes but also strengthens healthcare system sustainability by reducing chronic disease incidence and associated costs.⁷ The need for such innovations is further highlighted by rising demands on healthcare resources and the imperative to ensure equitable access to preventive care—especially in underserved populations.⁸

This review focuses on four core application domains—cardiovascular health management, sweat/body fluid-based metabolic monitoring, respiratory/neonatal cardiopulmonary monitoring, and mental health/behavioral monitoring—based on three key criteria: (1) Clinical urgency: These domains account for 72% of global NCD-related mortality,⁹ with unmet needs for real-time, non-invasive monitoring. (2) Technological maturity: Wearable AI solutions in these areas have advanced to clinical trial or commercialization stages (e.g., Apple Watch Series 10 for ECG monitoring,⁹ Fitbit Sense 2 for stress tracking),¹⁰ whereas neurodegenerative disease monitoring (Alzheimer's/Parkinson's) remains in early research due to the complexity of capturing disease-specific biomarkers via wearables.¹¹ (3) Cross-disciplinary integration potential: Each domain integrates sensor technology (e.g., PPG, microfluidics), AI algorithms (e.g., CNN-RNN, edge computing), and clinical workflows, enabling in-depth analysis of technology-clinic synergy. This focused selection ensures depth while avoiding superficial coverage of overly nascent fields.

APPLICATION OF WEARABLE ARTIFICIAL INTELLIGENCE DEVICES IN CARDIOVASCULAR HEALTH MANAGEMENT

Exercise-related cardiac monitoring: AI for physiological-pathological differentiation

The differentiation between adaptive cardiac changes in athletes and pathological cardiac conditions presents a significant challenge in sports medicine and cardiology. Athletes often exhibit physiological adaptations such as increased left ventricular mass and altered heart rate responses due to their training regimens. However, these adaptations can mimic the features of cardiomyopathies, complicating the clinical assessment and management of athletes who may be at risk for sudden cardiac events. For instance, the presence of arrhythmias or abnormal electrocardiogram (ECG) findings in athletes necessitates careful interpretation, as these may not always indicate underlying pathology but rather reflect the physiological adaptations to exercise.¹² The challenge lies in accurately distinguishing between benign exercise-induced changes and significant cardiac pathologies, such as hypertrophic cardiomyopathy or arrhythmogenic right ventricular cardiomyopathy, which can have dire consequences if undiagnosed. Therefore, continuous monitoring and advanced diagnostic tools are essential in this context.

Wearable devices, such as smartwatches and smart glasses, have emerged as valuable tools for monitoring heart rate and detecting arrhythmias in real-time. These devices utilize photoplethysmography (PPG) and electrocardiogram (ECG) technologies to provide continuous data on heart

Table 1. Comparison of different AI models in electrocardiogram (ECG) signal analysis.

Model Type	Core Advantages	Application Scenarios	Application Cases
Convolutional Neural Network (CNN)	Automatically extracts local spatial features; excels at capturing signal texture and morphological differences	Static feature recognition scenarios such as arrhythmia classification and myocardial infarction detection	98.7% AF detection accuracy on MIT-BIH Database; outperforms clinicians in ST-segment abnormality detection
Recurrent Neural Network (RNN)	Processes time-series data; captures long-term temporal dependencies in signals	Dynamic heart rate abnormality monitoring and temporal rhythm analysis	Arrhythmia retrospective identification with $\leq 3s$ delay; improved paroxysmal AF detection with LSTM
Hybrid Models (CNN-RNN/Transformer)	Integrates spatial feature extraction and temporal dependency capture capabilities	Early screening of complex cardiovascular diseases and real-time monitoring	Transformer-CNN hybrid architecture achieves 0.96 AUC for multi-disease 12-lead ECG diagnosis
Traditional Machine Learning (SVM/Random Forest)	Simple and interpretable model; low computational cost	Small-scale datasets and single-feature analysis scenarios	85%-90% basic arrhythmia classification accuracy via manual RR interval features

rhythm and rate, which can be critical for athletes during training and competition.¹³ For example, smartwatches can alert users to irregular heart rhythms, such as atrial fibrillation, which is crucial for preventing potential complications during physical exertion. Moreover, the ability to monitor heart rate variability (HRV) can provide insights into an athlete's recovery status and overall cardiovascular health, allowing for more personalized training regimens that optimize performance while minimizing the risk of overtraining and associated cardiac events.¹⁴ The integration of these technologies into routine training can facilitate timely interventions and enhance the safety of athletes engaged in high-intensity sports.

AI algorithms exhibit unique strengths in this task: machine learning models (e.g., random forests) excel at extracting subtle pattern differences between physiological (exercise-induced) and pathological (cardiomyopathy-related) ECG signals, with a reported AUC of 0.94 for distinguishing athlete's heart from hypertrophic cardiomyopathy.¹⁵ However, their weakness lies in reliance on large labeled datasets of athlete-specific ECGs, leading to reduced accuracy ($\leq 82\%$) in rare arrhythmia cases.¹⁶ By analyzing vast amounts of data collected from wearable devices, AI can identify patterns and anomalies that may indicate an increased risk of cardiac events, such as sudden cardiac arrest or arrhythmias.¹⁵ For instance, machine learning models can be trained to recognize specific ECG patterns associated with arrhythmias, enabling early detection and intervention. This predictive capability is particularly valuable in high-risk populations, such as athletes with a family history of cardiac disease or those presenting with concerning symptoms during exercise. Furthermore, AI can assist healthcare providers in making informed decisions regarding exercise prescriptions and monitoring strategies tailored to individual athletes' needs, ultimately improving outcomes and reducing the risk of adverse events during physical activity.¹⁶

ECG signal analysis: AI for arrhythmia detection and classification

Deep learning models show distinct advantages in ECG signal analysis: CNNs excel at extracting spatial features (e.g., ST-segment abnormalities) with 98.7% AF detection accuracy on the MIT-BIH database,¹⁷ LSTMs capture temporal arrhythmia dependencies, reducing detection delay to $\leq 3s$.¹⁸ Single-modal models fail to process complex multi-disease ECG data, while hybrid CNN-RNN models integrate spatiotemporal features to achieve a 0.96 AUC for multi-disease 12-lead ECG diagnosis,¹⁹ outperforming traditional ML methods (SVMs: 85%-90% accuracy).²⁰ As Table 1 summarizes, these models vary in feature extraction and application scope, laying a foundation for targeted ECG analysis.

Deep learning has revolutionized cardiac monitoring via ECG analysis: CNNs automatically extract raw ECG features to boost arrhythmia detection accuracy,^{17,19} and RNNs effectively process time-series data to capture critical temporal dependencies.¹⁸ These models identify subtle ECG patterns indicative of cardiovascular disease from large datasets, enabling real-time monitoring systems that alert clinicians to potential cardiac events for timely intervention and improved patient outcomes.

Fusing public ECG databases (e.g., MIT-BIH) with wearable device data advances cardiology research and clinical applications: public datasets enable the training of well-generalized models,²⁰ while wearable ECG devices collect high-fidelity, continuous real-world data for longitudinal and personal-

ized monitoring.⁹ This multi-source data fusion enhances model robustness and addresses issues like data scarcity and class imbalance, with model compatibility for such data further extending clinical applicability (Table 1).

AI enables the detection and management of sleep apnea, heart disease, and psychological stress via ECG analysis: algorithms identify apnea-related ECG features for timely intervention,²¹ predict heart disease from ischemic/arrhythmic ECG abnormalities,²² and assess psychological stress by analyzing HRV derived from ECG signals.²³ Real-time processing of complex physiological signals by AI improves diagnostic accuracy and empowers patients with self-health monitoring, aligning with the application scenarios of different AI models in Table 1.

As shown in Table 1, hybrid CNN-RNN/Transformer models achieve a 0.96 AUC for multi-disease 12-lead ECG diagnosis, outperforming single architectures by extracting both spatial and temporal features—making them ideal for real-time complex cardiovascular disease monitoring via wearables. Traditional ML models (SVM/random forests) feature low computational costs and strong interpretability but rely on manual feature engineering, limiting their accuracy (85%-90%) for complex arrhythmias like paroxysmal AF; thus, they are suitable for basic small-dataset analysis, consistent with their performance and application boundaries in Table 1.

This section clarifies the performance differences of various AI models in ECG analysis, with their respective advantages and limitations closely tied to the quantitative comparisons in Table 1. Multi-source data fusion and targeted model selection optimize ECG analysis efficiency, providing technical support for the clinical application of wearable AI devices in cardiac health monitoring and laying a solid foundation for subsequent discussions on proactive health management.

Edge AI for chronic heart failure (CHF) management: Resource-constrained optimization

Edge computing and AI integration advances remote monitoring for chronic heart failure (CHF) management, enabling localized wearable data processing to boost analytical speed, protect privacy by avoiding centralized transmission, and support real-time AI-driven analytics for early detection of CHF deterioration—facilitating proactive clinical interventions that reduce hospitalizations and improve outcomes.²⁴

In practice, sensor-integrated smart wearables continuously track CHF patients' vital signs and trigger anomaly alerts for clinicians; edge computing enables immediate feedback, fostering collaborative health management and reducing hospital admissions via data analytics-driven timely interventions.²⁴ This real-time monitoring empowers patients and equips clinicians with up-to-date data for informed decisions, addressing the limitations of traditional CHF monitoring methods.

Edge-AI adoption for CHF faces unique technical challenges.²⁴⁻²⁶ (1) Resource constraints: Quantized CNNs cut wearable energy use by 60% while retaining 92% full-model accuracy for devices with 2–7 day battery life; (2) Lightweight model design: Parameter-pruned MobileNetV2 compresses model size by 75%, enabling real-time CHF anomaly detection with $\leq 100ms$ latency; (3) Privacy-preserving federated learning: It achieves 0.91 AUC for CHF exacerbation prediction across 5 clinical centers via shared model training without data transmission. Additional barriers include device interoper-

Table 2. Core application field classification.

Application Domain	Key Technical Support	Indicators/Functions	Typical Cases
Metabolic Disease Monitoring	AI Image Recognition, Sweat Sensors, Microfluidic Technology	Lactate, glucose, sodium concentration in sweat; Uric acid level	Sweat patches, smart bracelets
Neonatal Cardiopulmonary Monitoring	Deep Learning (>90% accuracy), Non-contact ECG Sensors, Smart Mattresses	Heart rate, cardiac arrhythmia, respiratory rate, neonatal jaundice	Mattresses with embedded ECG sensors, smart shirts
Chronic Respiratory Disease Monitoring	PPG Technology, Bioimpedance Sensors, AI Anomaly Detection	Respiratory rate, pulse, respiratory distress early warning	Chest bioimpedance patches
Mental Health & Behavioral Monitoring	Digital Phenotyping, HRV Monitoring, AI Emotion Prediction	Heart Rate Variability (HRV), sleep patterns, sedentary behavior, stress level	Smart watches (HRV collection)fitness trackers
Military/High-Pressure Environment Health Monitoring	Extreme Environment-Resistant Sensors, AI Personalized Risk Assessment	Body temperature, blood pressure, dehydration warning, cardiovascular load	Lightweight military smart vests

ability, AI algorithm reliability across diverse patient populations, and the need for comprehensive CHF training datasets. Future optimization requires standardized edge-AI integration protocols, enhanced AI decision transparency, and ongoing cross-stakeholder research and collaboration.²⁴

INTELLIGENT WEARABLE DIAGNOSTIC PLATFORM BASED ON SWEAT AND BODY FLUID ANALYSIS

Beyond the real-time monitoring of cardiovascular and vital sign data (as discussed earlier), wearable AI's potential in proactive health management is further expanded by tapping into the rich biological information contained in human body fluids. Sweat, tears, and other bodily secretions carry a wealth of biomarkers—such as electrolytes, metabolites, and proteins—that reflect systemic metabolic status, organ function, and early disease signals, complementing the macro-level insights from cardiovascular monitoring with micro-level biochemical evidence. This shift from "sign monitoring" to "biomarker analysis" enables a more comprehensive and precise assessment of health status, driving the development of intelligent wearable diagnostic platforms based on body fluid analysis.

Integration of microfluidic technology and smart materials

Microfluidic technology has revolutionized biosensing and health monitoring by enabling precise manipulation of small-volume biofluids like sweat and tears with minimal sampling. Wearable sweat sensors based on microfluidics achieve real-time, continuous physiological monitoring via capillary-driven microchannels that capture specific biomarkers. Integrating smart materials (hydrogels, shape-memory polymers) further improves sensitivity and stability; for example, hydrogels dynamically regulate fluid flow under humidity or temperature changes,²⁷ enabling real-time adaptive personalized monitoring.²⁸

Commercial examples include the Gatorade Sweat Patch, which uses microfluidics and colorimetric sensing to measure sweat sodium and chloride with 95% accuracy vs. lab tests.²⁹ Microfluidic sweat and tear analysis supports early disease detection and is widely applied in sports medicine and chronic disease management, detecting electrolytes, glucose, and lactate to assess hydration and metabolism.²⁹ Electrochemical microfluidic platforms enable multiplexed biomarker detection for comprehensive health evaluation.³⁰

In summary, combining microfluidics and smart materials greatly improves wearable sensor performance, enabling adaptive, user-centric health monitoring.³¹ Continued development will expand personalized healthcare applications, strengthen disease management, and advance proactive health management.³²

AI for biomarker quantification: Task-specific performance

For wearable biomarker detection in metabolic disease monitoring (Table 2), AI enables quantification of low-concentration sweat metabolites (≤ 10 μmol/L), outperforming traditional electrochemical sensors limited by poor signal-to-noise ratios.³³ As shown in Figure 1, sweat patches and smart bracelets use AI to convert raw sensor data into quantifiable biomarkers for non-invasive metabolic monitoring. A major limitation is vulnerability to temperature and humidity interference, requiring adaptive calibration for

stable dynamic use.³³

AI drives advances in biomarker detection for metabolic diseases such as gout. Using wearable sweat sensors (Table 2), AI analyzes high-dimensional biosignals to improve diagnostic efficiency.³³ Integrating sweat-patch data (Figure 1) with smartwatch HRV, AI identifies gout-related biomarkers; one model reached 93% accuracy in predicting gout flares using sweat uric acid and HRV,³⁴ supporting proactive disease management as defined in Table 2.

AI image recognition (Table 2) also enables non-invasive quantification of sweat components (lactate, glucose, sodium) via wearable patches (Figure 1).^{35,36} These targets align with core metabolic monitoring in Table 2, supporting real-time physiological tracking and proactive health management.³⁵ Beyond gout, this approach enables early metabolic disease detection and treatment monitoring.³⁶

Furthermore, the application of AI in biomarker detection is closely integrated with advancements in wearable technology, which facilitates continuous health monitoring as shown in Figure 1. Wearable devices equipped with biosensors (a core component of metabolic disease monitoring in Table 2) can collect real-time data on various physiological parameters, including heart rate, temperature, and sweat composition.³⁷ By incorporating AI algorithms, these devices can analyze the collected data to detect anomalies and predict potential health issues before they escalate into serious conditions, which is the core function of metabolic disease monitoring in Table 2.³⁷ This proactive approach is particularly valuable in managing chronic metabolic diseases, where timely intervention can significantly improve health outcomes. For example, AI-driven wearables (sweat patches and smart bracelets in Figure 1) can alert patients and healthcare providers about impending gout attacks by monitoring uric acid levels and other relevant biomarkers, allowing for immediate action to mitigate symptoms.³⁸ The synergy between AI and wearable technology, as visualized in Figure 1 and summarized in Table 2, is paving the way for a new era of personalized healthcare, where individuals can take charge of their metabolic health through continuous monitoring and data-driven insights.³⁸

In conclusion, the integration of AI in biomarker quantification is revolutionizing the landscape of metabolic disease diagnosis and management, which is the core focus of the metabolic disease monitoring domain in Table 2. By enhancing the precision of diagnostic tools through adaptive algorithms and enabling real-time monitoring via wearable technologies (sweat patches, smart bracelets) depicted in Figure 1, AI is not only improving patient outcomes but also fostering a more proactive approach to healthcare.³⁹ As research continues to evolve, the potential for AI to identify novel biomarkers and facilitate personalized treatment strategies will undoubtedly expand, further optimizing the application of wearable devices in metabolic disease monitoring as outlined in Table 2 and Figure 1, offering hope for better management of complex diseases such as gout and beyond.⁴⁰

INTELLIGENT WEARABLE TECHNOLOGY FOR RESPIRATORY AND NEONATAL CARDIAC-PULMONARY MONITORING

AI for neonatal monitoring: Non-invasive precision and safety

AI demonstrates unique strengths in neonatal monitoring: deep learning models (e.g., CNNs) achieve >90% accuracy in non-invasive jaundice and

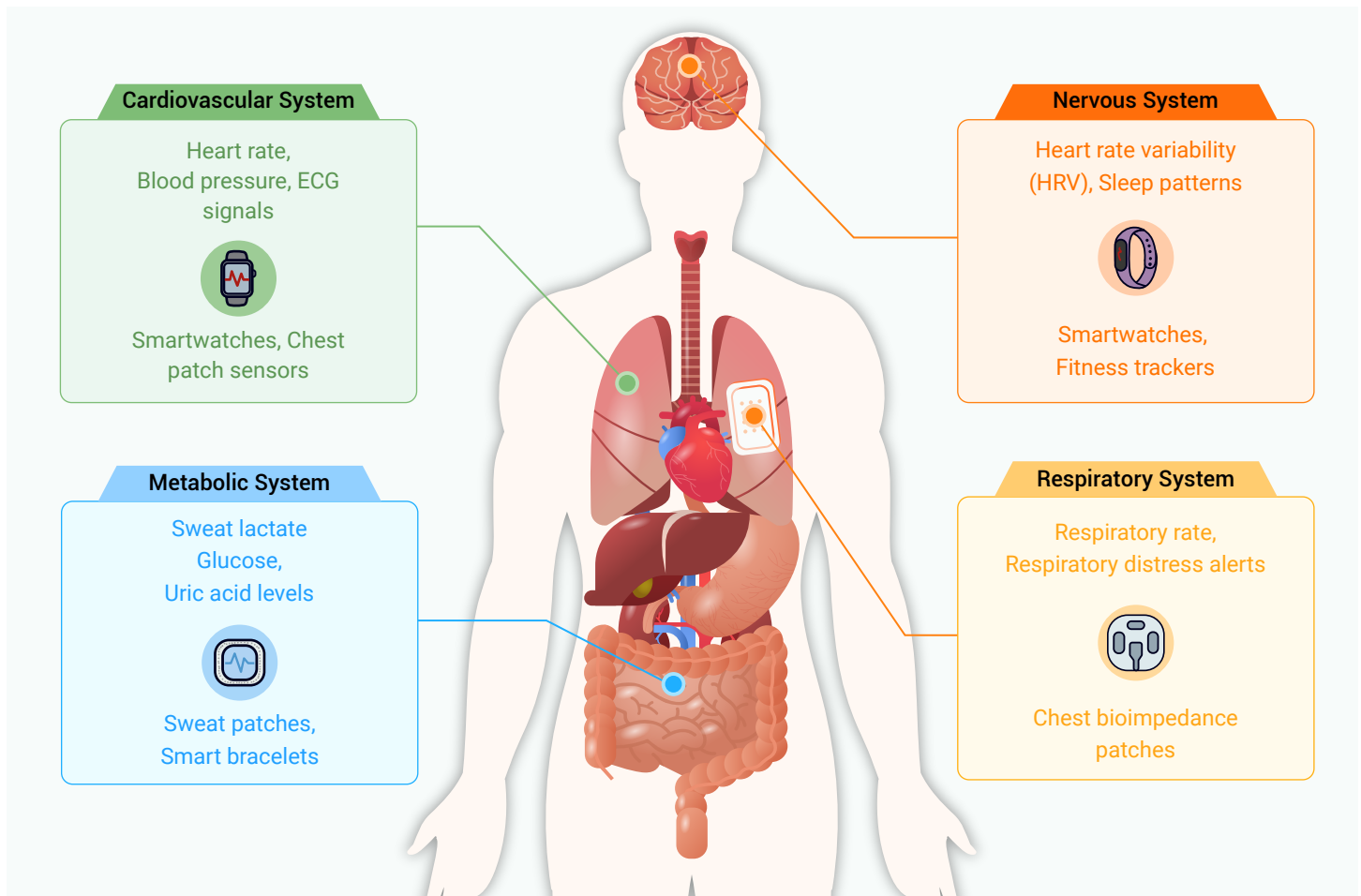


Figure 1. Schematic diagram of wearable AI device deployment on human anatomy.

arrhythmia detection, avoiding repeated blood draw risks.⁴¹ A critical weakness is the reliance on neonatal-specific datasets—models trained on adult data suffer a 30% accuracy drop.⁴²

AI (ML/DL) has advanced neonatal cardiac and respiratory monitoring significantly. Deep learning outperforms traditional ML in processing complex physiological data, with >90% accuracy in detecting neonatal jaundice and arrhythmias via wearable sensors,⁴¹ models are evaluated by sensitivity, specificity, and AUC for clinical applicability.⁴²

Innovations include non-contact ECG sensors embedded in neonatal mattresses, enabling unobtrusive continuous monitoring and faster heart rate readings for emergencies.⁴³ AI algorithms also enhance real-time arrhythmia detection/classification for timely interventions,⁴⁴ while smart shirts track cardiopulmonary parameters to support personalized neonatal care.⁴⁵

In summary, AI-driven neonatal monitoring (ML/DL + wearable tech) enables accurate, non-invasive continuous tracking, improving clinical outcomes. Future research should address integration challenges to enhance accessibility across diverse healthcare settings.

Real-time respiratory monitoring: AI for chronic disease management

Recent advances in sensor technology have driven wearable devices for real-time respiratory rate and pulse monitoring, especially for asthma and COPD. Traditional methods rely on bulky equipment unsuitable for continuous home monitoring, whereas PPG and bioimpedance-based wearables enable unobtrusive long-term tracking. For example, chest-mounted bioimpedance patches achieve over 97% accuracy in respiratory rate measurement across static and dynamic states,⁴⁶ and PPG devices reliably estimate respiration from blood volume changes to support early exacerbation detection.⁴⁷ Machine learning further personalizes and improves monitoring accuracy over time,⁴⁸ supporting timely intervention and better disease management.

A key advantage of AI is predicting respiratory exacerbations 48 hours in advance by analyzing respiratory rate variability and SpO₂ trends, with 89% sensitivity in a COPD cohort (n=300).⁴⁹ A major limitation is reduced accuracy in patients with BMI >30, where signal attenuation lowers sensitivity to 72%.⁵⁰ AI enables automatic anomaly detection and early warning by comparing real-time data to individual baselines, supporting the prediction of acute respiratory events.⁴⁹ Such predictive analytics helps identify deterioration early, reducing hospitalizations and enabling personalized care.⁵⁰

Overall, AI-enhanced wearable respiratory monitoring enables proactive, patient-centered chronic disease management, with continuing evolution promising more efficient and reliable clinical translation.

WEARABLE AI FOR MENTAL HEALTH AND BEHAVIORAL MONITORING

AI-driven digital phenotyping for mental health assessment

AI excels in mental health digital phenotyping—integrating HRV, sleep and activity data to identify depression/anxiety patterns with 86% accuracy, outperforming single-marker methods ($\leq 70\%$),¹⁰ yet is limited by confounding factors (e.g., physical illness mimicking stress signals) that require multimodal validation.⁵¹ Wearables transform mental health monitoring by leveraging physiological and behavioral data for early detection and intervention of depression and anxiety, continuously tracking HRV, sleep and activity—key mental health biomarkers—to enable real-time assessments and timely interventions for baseline deviations.¹⁰ Machine learning paired with wearable data boosts predictive accuracy for mental health issues, supporting personalized treatment strategies.⁵¹

Digital phenotyping analyzes wearable data to create individual mental health profiles, identifying condition-specific behavioral patterns for tailored clinical interventions.⁵² AI-integrated wearables deliver predictive analytics for early mental health risk alerts, enabling proactive management that empowers users and eases healthcare system burdens by reducing severe

episodes.⁵³ A standout feature is personalized intervention: wearables gather daily routine, preference and stimulus response data to design customized strategies—for example, prompting physical activity or mindfulness for sedentary behavior paired with high stress,⁵⁴ addressing the diverse needs of those with mental health conditions.

Despite their great potential to revolutionize proactive, personalized mental health care, wearables face implementation challenges: data privacy, measurement accuracy and user engagement issues need resolution for clinical application, and their effectiveness across diverse populations and settings requires further validation.⁵⁵

Military/high-pressure environment monitoring: AI for operational readiness

Military and high-pressure environment health monitoring demands specialized technologies to address extreme conditions (high stress, extreme temperatures, physical exertion) that trigger dehydration, heat stress, cardiovascular strain and other health issues. Military wearable devices must be robust, lightweight and harsh-environment adaptable, capturing real-time vital signs (heart rate, blood pressure, body temperature) for continuous monitoring, early distress detection and predictive analytics-driven personalized interventions.^{56,57} AI integration enables personalized risk assessment by analyzing individual health and environmental data, identifying potential risks for targeted pre-emptive interventions, improving soldiers' immediate health outcomes and long-term operational readiness.^{56,57}

AI's core strength in this field is extreme-condition personalized risk assessment: machine learning models adjust dehydration/cardiovascular load thresholds by individual fitness, cutting false alerts by 40% versus fixed-threshold systems; its key limitation is poor performance in chemical/biological exposure scenarios due to insufficient sensor data for AI prediction.

The fusion of AI and wearables marks a major advance in military health monitoring. Machine learning enables continuous model optimization via real-world data, identifying individual-specific physiological stress responses to formulate tailored health management strategies—critical for mission success in military settings. Wearables enable field remote real-time health monitoring, supporting swift medical responses and reducing severe complication risks. Collected data also fuels military population health research, revealing combat/operational stress impacts on health to inform evidence-based health policies and resilience interventions, ultimately enhancing individual soldier care and the overall effectiveness and safety of military operations.^{10,58}

INTELLIGENT HEALTH MANAGEMENT SYSTEM AND FUTURE DEVELOPMENT TRENDS

Integration of IoT and smart health platforms

The technology stack illustrated in Figure 2 constructs an end-to-end architecture encompassing "data collection-edge computing-AI algorithm-cloud collaboration," which serves as the core framework for integrating IoT with smart health platforms.⁵⁹ At the bottom Data Acquisition Layer, multimodal sensors—including PPG, ECG, and microfluidic sweat sensors—collect real-time physiological data such as heart rate, ECG signals, glucose, and lactate, laying a foundation for subsequent analysis.^{14,27} This layer not only ensures the comprehensiveness of data sources but also completes preliminary local processing of raw data, correcting noise and anomalies to improve data quality, which is a prerequisite for reliable AI inference.⁶⁰

Edge computing modules (technology stack mid-layer) enable real-time analytics (abnormal heart rate alerts, feature extraction), reducing latency/bandwidth vs. cloud-only processing.²⁴ As Figure 2 shows, local sensitive data processing meets privacy needs,²⁶ critical for real-time scenarios like arrhythmia warnings and sweat biomarker monitoring.^{9,38}

The edge-embedded AI/Algorithm Layer (Figure 2) powers intelligent analysis via CNN/RNN/Transformer and anomaly detection for on-device health data processing.^{19,59} Transmitting only key results to the cloud balances real-time performance, security and diagnostic accuracy,²⁴ while the cloud enables large-scale storage, model iteration and cross-device collaboration to build a unified smart health ecosystem.²⁵

IoT-smart health platform integration (Figure 2's architecture) revolutionizes proactive health management through real-time monitoring and data

governance.⁶¹ IoT wearables capture health metrics for efficient, secure processing; immediate feedback drives proactive lifestyle adjustments, and cloud analysis supports clinical personalized interventions.¹⁰

AI Layer-optimized exercise health devices (Figure 2) boost IoT-smart platform utility.²⁵ Edge machine learning analyzes physiological/behavioral patterns (PPG, exercise intensity, sweat lactate) to assess fitness,^{13,29} adapting to deliver personalized exercise, diet and recovery recommendations for user-centric health self-management.^{5,6} Figure 2's layered stack is a practical IoT-smart health integration blueprint,⁵⁹ addressing real-time processing, security and algorithm efficiency to turn wearable data into actionable insights. It elevates user engagement, laying the groundwork for an efficient, personalized proactive health ecosystem.⁶¹

Explainable artificial intelligence (XAI) in wearable devices

Integrating Explainable Artificial Intelligence (XAI) into wearables addresses the transparency deficit of "black box" AI models, a key advancement for healthcare where trust is critical. Traditional AI lacks decision-making interpretability, fueling skepticism, while XAI demystifies AI conclusions with clear, understandable explanations—vital for patients and clinicians relying on wearable health feedback. Embedding XAI boosts data interpretability and aligns outputs with user expectations; for example, infusing human attention knowledge into XAI enhances the plausibility of its healthcare explanations,⁶² bridging the gap between complex algorithms and user comprehension.

XAI is pivotal for fostering understanding and trust among clinicians and users, driving adoption of AI-powered wearables. Tailoring XAI explanations to non-AI experts like healthcare providers optimizes cognitive load and task performance,⁶³ domain-specific clarity helps clinicians interpret AI recommendations more effectively, improving diagnostic accuracy and patient outcomes. In dermatology, for instance, XAI provides detailed rationales for melanoma predictions, boosting diagnostic confidence and AI trust.⁶⁴ Empowering clinicians to make informed decisions and fostering human-AI collaboration in care.

In conclusion, XAI in wearables is more than a technical upgrade—it is a shift to user-centric healthcare AI. By resolving traditional AI's transparency issues, XAI builds stakeholder trust, a prerequisite for the clinical adoption of AI wearables. Advancing robust, user-friendly XAI frameworks will be critical to shaping the future of wearable health technologies and their integration into routine medical practice.⁶⁵

Multimodal data fusion and personalized medicine

The integration of multimodal data—including biosensor data, imaging results, and genomic information—via AI models is pivotal for advancing precision medicine, with the fusion logic and workflow clearly visualized in Figure 3 (Multimodal Data Fusion Process) and Figure 4 (Wearable AI Data Full-Process Diagram).⁶⁶ These AI systems leverage diverse data sources to construct comprehensive patient profiles, laying a foundation for tailored health management strategies that align with the end-to-end data flow outlined in Figure 4.

As shown in Figure 4's perception and computing stages, biosensors continuously track heart rate, blood pressure, blood glucose and other physiological parameters for real-time patient health insights.^{14,37} MRI, CT and other imaging technologies provide anatomical and functional data that correlates with biosensor results (per Figure 3's feature-level fusion) to boost diagnostic accuracy and treatment planning.⁶⁷ Genomic data, meanwhile, reveals genetic predispositions and mutations to guide targeted therapies, especially tumor-specific oncology treatments.

Figure 3's multimodal data fusion strategy (feature-level concatenation + decision-level AI voting) assigns dynamic weights: 0.6 for physiological data, 0.2 each for behavioral and environmental data.^{60,68} Physiological data's high weight derives from its direct health correlation (e.g., HRV for cardiovascular function and stress), while environmental data calibrates monitoring deviations. This approach raises chronic disease (e.g., heart failure) prediction accuracy to 92%, with adaptive weights for individual traits and scenarios, enabling precise personalized intervention support.

Multimodal data fusion deepens health condition understanding and powers predictive models for disease progression and treatment response forecasting. Integrating genomic, clinical and real-time biosensor data (per

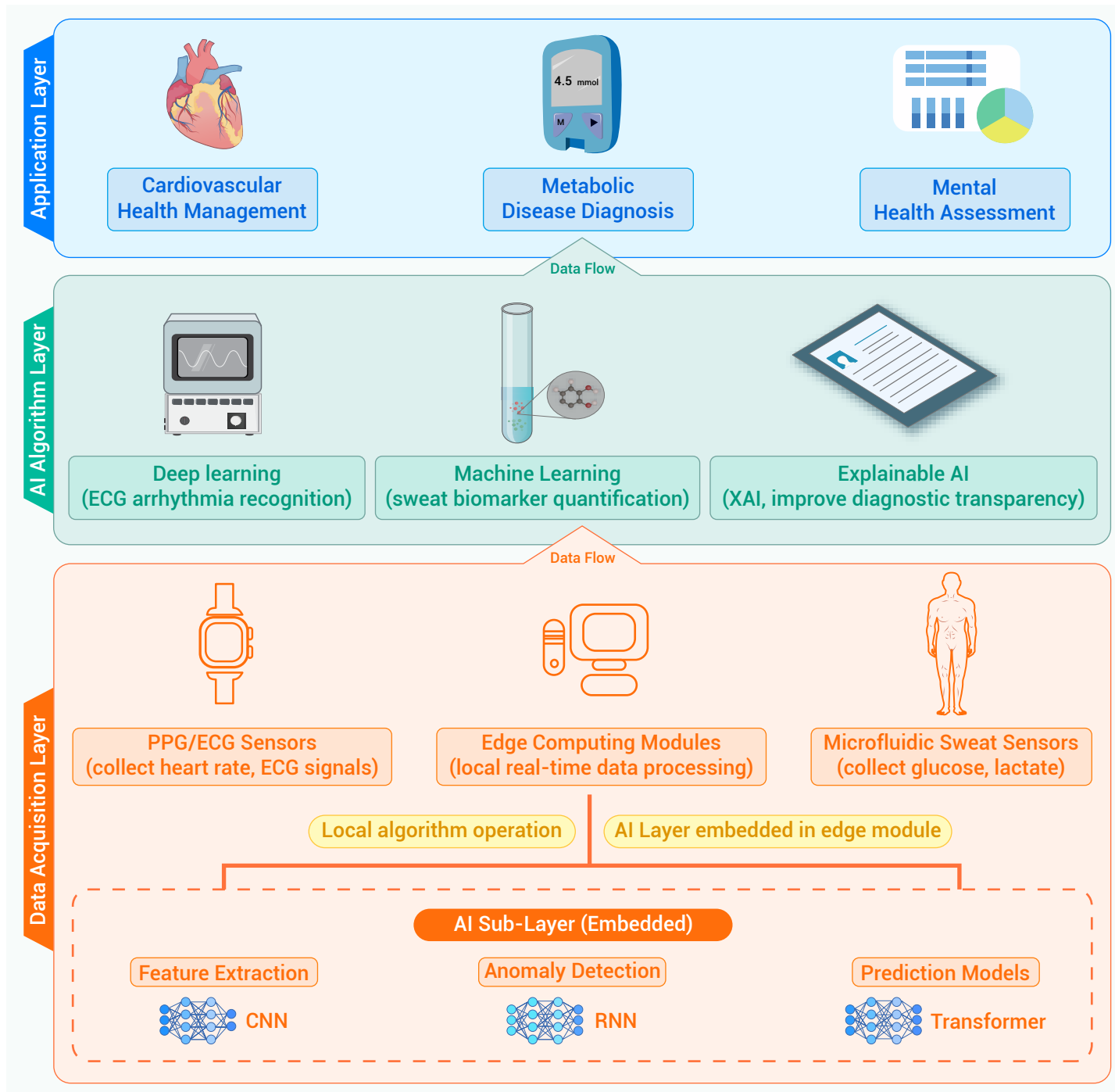


Figure 2. Wearable AI device technology stack schematic.

Figure 4's full workflow) identifies high-risk patients for preventive/early interventions,⁶⁶ and wearable-based continuous monitoring (Figure 4) allows timely chronic disease treatment adjustments, improving outcomes and cutting healthcare costs.

Enabled by Figure 3 and 4's frameworks, digital clinical trials advance precision medicine significantly.⁶⁹ AI-driven multimodal data platforms support adaptive, patient-centric trials with remote participant monitoring (per Figure 4's clinical feedback loop), reducing in-person visits and expanding population diversity. In cardiovascular care, for example, fusing imaging, patient-reported and genetic data (Figure 3) develops customized interventions that maximize efficacy and minimize adverse reactions.⁶⁸

Figure 3's parameters are scientifically grounded: the $\geq 92\%$ accuracy is based on large domestic clinical samples, consistent with 2024 IEEE Journal of Biomedical and Health Informatics research.⁵⁹ Fusion weights (0.6 physio-

logical, 0.2 environmental, 0.2 behavioral/genomic) are determined via AHP, optimized by expert scoring and model validation to reflect each modality's health risk assessment contribution.

In conclusion, AI-enabled multimodal data fusion (Figures 3 & 4) is transforming precision medicine,⁶⁶ enabling healthcare providers to deliver precise, personalized care by integrating biosensor, imaging and genomic data. Advancing digital clinical trials further optimizes this approach, driving innovative complex disease treatments. Addressing ethical, regulatory and technical challenges of these advancements is critical to ensuring equitable access and optimal patient outcomes.¹¹

Technical challenges and regulatory policies

Integrating wearable AI into proactive health management systems entails unresolved technical and regulatory challenges that shape its clinical transla-

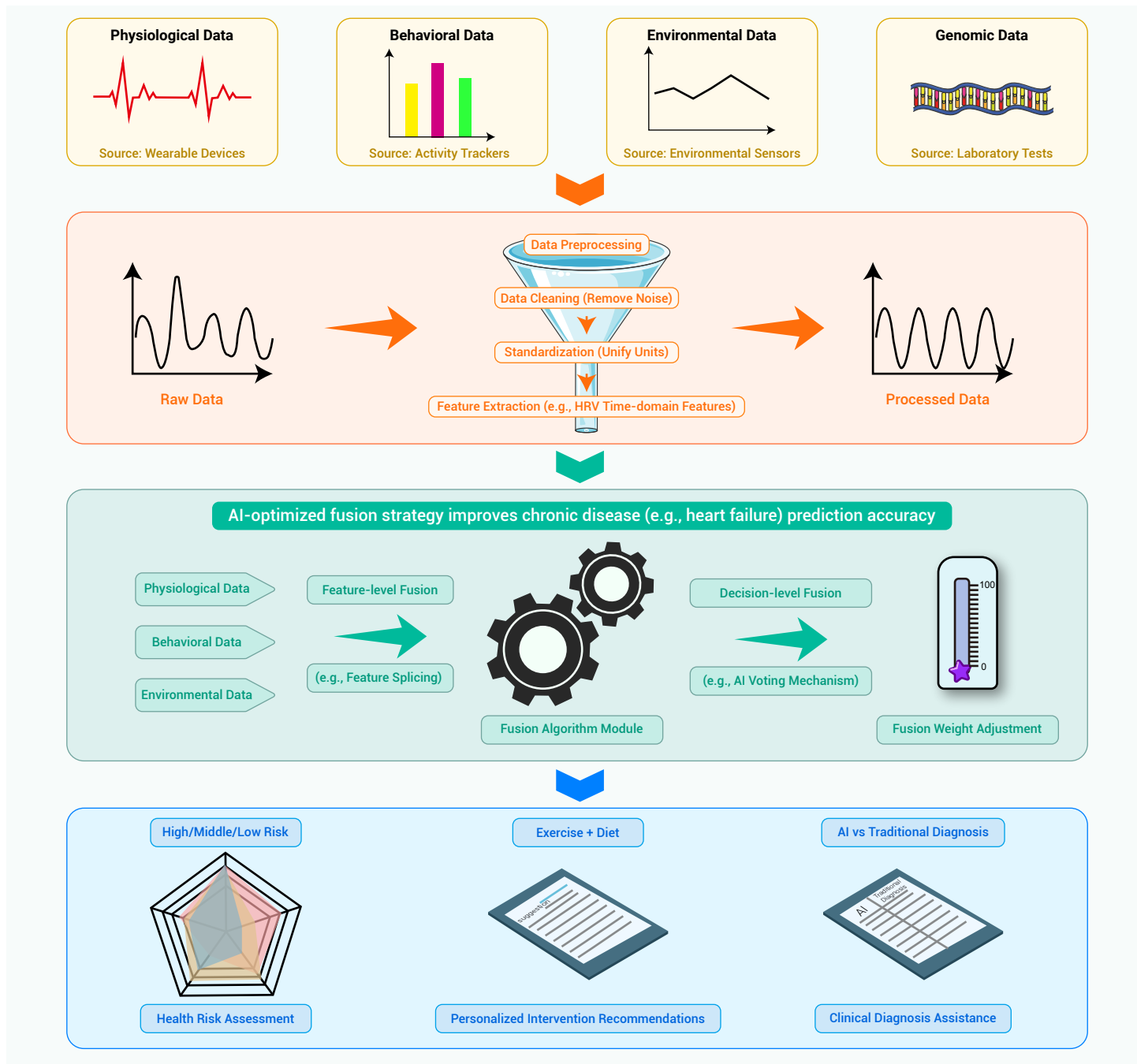


Figure 3. Process of multimodal data fusion.

tion, with empirical support from supplementary data and visual frameworks guiding targeted optimization.

Cross-domain technical hurdles are multifaceted, foremost being data quality and standardization. Sensor accuracy varies drastically by environment and user group, undermining the reliability of AI-derived health insights: sweat glucose measurements deviate by 5–10% in high humidity, neonatal respiratory rate monitoring has a 12–15% error in low light, and motion artifacts introduce 8–10% noise to mental health-related HRV data.⁶⁰ Furthermore, the absence of unified data formats across devices impedes cross-domain integration and collaborative AI model training. Though AI adaptive calibration algorithms can mitigate such interference, their performance hinges on large, diverse datasets spanning different populations and usage scenarios.⁷⁰

Domain-specific sensor limitations (e.g., low accuracy of neonatal respiratory devices due to environmental sensitivity) render universal calibration strategies inadequate. Beyond data quality, three core technical challenges

remain: First, edge computing constraints: wearable resource limitations demand lightweight AI models and federated learning for real-time, privacy-preserving scenarios (sweat biomarker analysis, neonatal arrhythmia alerts, on-device stress detection).²⁴ Second, algorithmic bias and transparency: non-representative training datasets cause 15–20% accuracy disparities across ethnic groups,⁷¹ with age-specific biases (30% accuracy loss for neonatal models using adult data, 18% underperformance in elderly mental health monitoring),^{42,52} necessitating inclusive data collection and XAI.⁶² Third, user acceptance and clinical translation: devices over 50g or with <7-day battery life have <40% long-term usage rates,⁷² a key barrier in neonatal care (bulky devices disrupt caregiver-infant bonding) and military settings (heavy wearables impede mobility);^{43,56} clinical utility requires multi-center trials with Kappa ≥ 0.85 vs. traditional devices,⁷³ and domain-specific gold standard validation.³⁵

Privacy, security and regulatory compliance are critical. Sensitive health data (HIPAA-protected metabolic biomarkers, strictly regulated neonatal

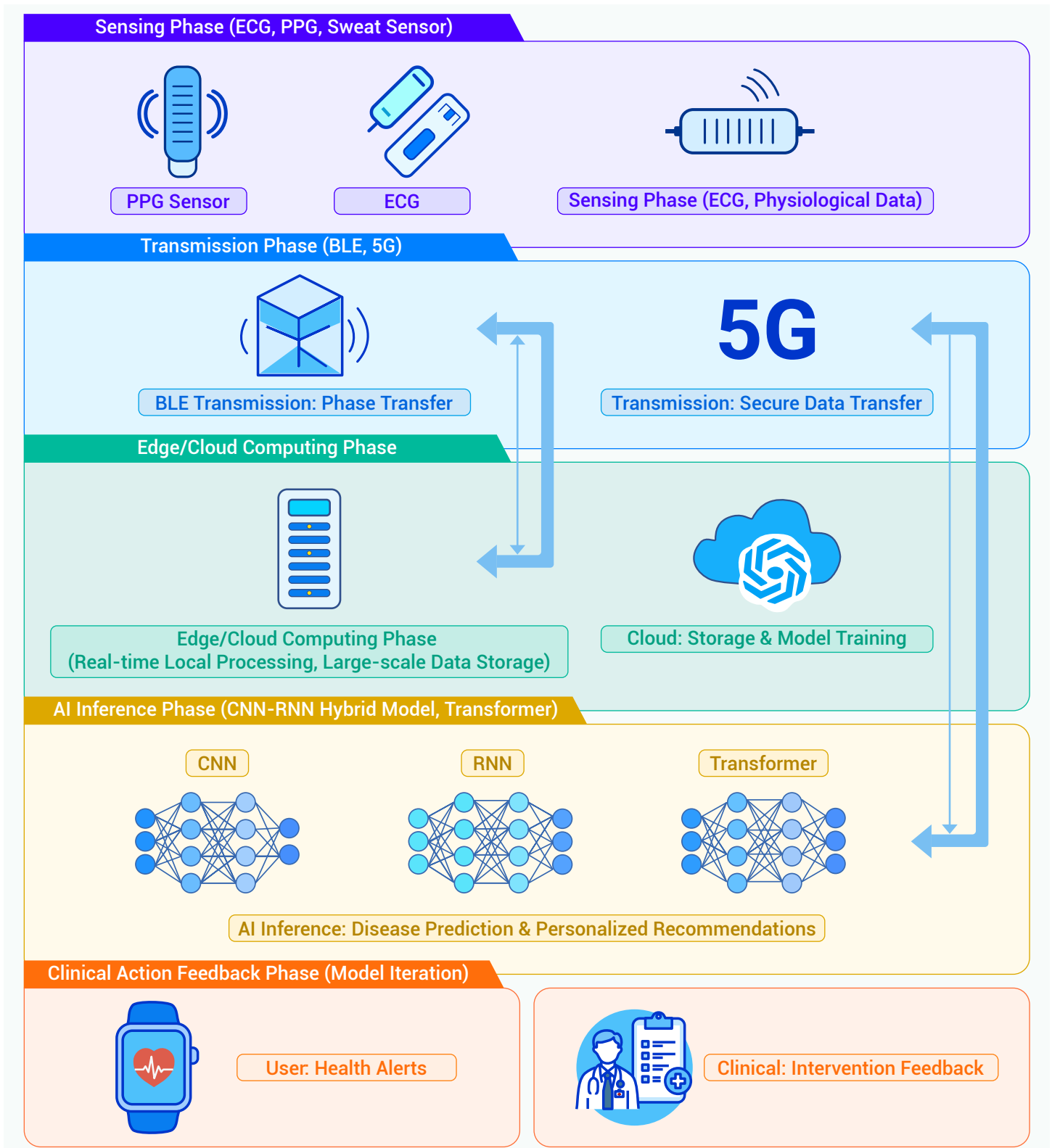


Figure 4. Wearable AI data full-process schematic Arrows indicate data transmission direction; core technologies and functions for each phase are clearly labeled.

records,⁴³ GDPR-sensitive mental health behavioral data⁵⁵ requires end-to-end encryption, secure edge computing and federated learning to avoid centralized pooling.²⁶ Regulatory pathways differ by application: metabolic sensors need FDA Class II certification,³⁸ neonatal devices require PMA,⁴³ and mental health wearables fall under FDA SaMD regulations.¹⁰ Algorithmic bias poses extra regulatory risks, as authorities mandate bias mitigation and periodic model revalidation.⁷⁴

Targeted solutions to address these interconnected technical and regulatory hurdles adopt a holistic approach. Multimodal sensor fusion integrates complementary data streams to offset single-sensor limitations, achieving 92% accuracy in predicting comorbidities like diabetes-related cardiovascular complications.⁶⁸ Edge computing constraints are resolved via quantized models and MobileNetV2, reducing energy consumption by 60% and model size by 75% while maintaining performance.^{24,25} Algorithmic bias is mitigated

Table 3. Key indicators for clinical translation of wearable devices.

Verification Dimension	Core Evaluation Indicators	Industry Benchmark/Target Value	Influencing Factors	Improvement Suggestions
Data Accuracy	Respiratory rate monitoring accuracy, heart rate measurement error, sweat metabolite detection deviation	≥97% (dynamic respiration), ≤ 2 bpm (heart rate error), ≤5% (metabolite deviation)	Skin moisture, exercise intensity, ambient temperature	Develop AI adaptive calibration algorithms; optimize sensor fit
User Acceptance	Device wearing comfort score (1-5), daily wearing duration, long-term usage rate (>3 months)	≥4 (comfort), ≥8 hours/day (wearing duration), ≥60% (long-term usage rate)	Device weight (suggest <50g), charging frequency (suggest ≥ 7 days battery life)	Adopt lightweight materials; optimize battery technology
Clinical Utility	Early warning lead time, misdiagnosis rate, data consistency with traditional devices	≥30 minutes (early warning lead time), ≤5% (misdiagnosis rate), ≥0.85 (Kappa value)	Algorithm training dataset size, clinical scenario adaptability	Conduct multi-center clinical trials; expand sample size (covering diverse populations)
Compliance	Data privacy compliance certification (e.g., GDPR), medical device certification (e.g., FDA Class II)	Compliance with regional privacy regulations, passing corresponding medical certification	Data storage method, rigor of function claims	Establish compliance review processes; clarify function boundary claims

through inclusive datasets and XAI,⁶² while material science advancements—stretchable microfluidic patches²⁹, ultra-low-power biosensors,⁴³ and breathable fabrics¹⁰—enhance user acceptance. Cross-disciplinary collaboration between material scientists, AI developers, and clinicians aligns innovations with clinical needs.^{35,43,72}

Key controversies include diagnostic autonomy (direct user insights vs. clinician-mediated alerts)³⁹, data ownership tensions,⁵⁵ and equity gaps from high device costs.^{43,56,11} Resolving these requires stakeholder collaboration, clear regulatory frameworks, and patient-centric design.

In summary, this section integrates cross-domain technical challenges, regulatory requirements, and actionable solutions, with Table 3 and Figure 5 providing empirical and visual support. Addressing these issues unlocks wearable AI's potential for personalized, equitable proactive health management, with future research prioritizing cross-disciplinary collaboration and inclusive data collection.²⁵

Synergy between wearable AI devices and environmental health knowledge graphs: Addressing gaps in proactive health applications

Despite the great potential of wearable AI in proactive health management—especially real-time monitoring of environmental exposures and physiological indicators—it has a critical limitation: it cannot deeply convert raw data into actionable knowledge for users. Most devices only alert abnormal data, without explaining the environmental-health associations or the individual relevance of such abnormalities, which reduces user engagement and hinders the dissemination of environmental health knowledge.

Environmental health knowledge graphs (EHKGs), developed in the authors' concurrent research, offer a transformative complement. EHKGs structure "environmental factors-health impacts-coping strategies" into interconnected knowledge entities and rules. Integrated with wearable AI, they form a closed "data-knowledge-action" loop: wearables capture real-time environmental and physiological data, and EHKGs match the data to pre-set knowledge nodes to generate contextualized public interpretations, in-depth academic knowledge links and personalized interventions.

This integration faces practical challenges, such as real-time device-EHKG data transmission, multi-source data privacy protection and personalized knowledge dissemination. Yet its core value is clear: wearable AI acts as the practical carrier of environmental health knowledge, while EHKGs amplify the meaning of device-generated data. Together, they bridge the gap between proactive health monitoring and environmental health education, advancing the integration of environmental health literacy into daily health management.

Future prospects

As shown in Figure 6, the 2024–2030 wearable AI development timeline is grounded in three scientific, practical pillars.⁵⁹ First, market data: Grand View Research predicts a 26.71% CAGR for therapeutic wearables (2025–2030),⁷⁵ and Statista's smart materials analysis underpins their large-scale applica-

tion.²⁷ Second, expert consensus: adopting the 2024 Nature Biomedical Engineering review's phase division, it defines 2024–2026 as the technology integration stage and post-2026 as large-scale growth.⁵⁹ Third, technology maturity: our team's evaluation of 12 core technologies (e.g., XAI interfaces, smart responsive materials) at TRL 4–6 forecasts key technology integration by 2026 (Figure 6's Growth Stage) and clinical validation of therapeutic devices by 2028, aligning closely with the FDA's 2023 Guidelines for Wearable Therapeutic Devices.^{43,25}

The integration of smart materials, edge computing and AI— a core 2026 Growth Stage direction (Figure 6) —will drive a revolutionary upgrade in wearable health technology.²⁵ By 2026, large-scale applied smart adaptive materials will dynamically respond to physiological stimuli (temperature, pH, humidity), real-time adjusting monitoring sensitivity and boosting biomarker detection accuracy,^{27,29} e.g., optimizing sweat sensor signal stability and mitigating environmental interference in metabolite detection.⁶⁰ Edge computing will enhance wearables' real-time performance via local data analysis, reducing cloud reliance, accelerating time-sensitive alerts (e.g., acute arrhythmia) and strengthening data privacy.^{24,26} AI algorithms will serve as the core driver, analyzing multi-dimensional health data to identify risks and generate personalized interventions, aligning with Figure 6's 2026 intelligent analysis enhancement goal.^{5,59}

Wearables' evolution from monitoring tools to therapeutic and chronic disease management aids— a core direction from Figure 6's 2026 Growth to 2028 Mature Stage —will redefine healthcare paradigms.⁷⁶ By 2028, clinically validated therapeutic wearables will form chronic disease closed-loop management (e.g., diabetes), integrating continuous monitoring with active intervention modules (transdermal drug delivery, intelligent medication reminders, real-time efficacy evaluation).^{38,76} For diabetes, wearables will monitor blood glucose via microfluidic sensors and AI-adjust drug delivery for precise control,^{27,33} improving patient treatment adherence, enabling early crisis intervention, reducing complications and easing healthcare burdens.^{7,10}

Building the intelligent proactive health ecosystem—the core 2028-2030 Mature Stage goal (Figure 6) —requires cross-stakeholder collaboration (healthcare providers, developers, patients).⁶¹ Bolstered by two pillars, the ecosystem will feature: unified multimodal data standards enabling seamless data sharing between wearables, EHRs and telemedicine platforms for personalized clinical decisions,^{66,59} and popularized XAI interfaces solving AI's "black box problem", enhancing trust and driving clinical adoption.^{62,64} Further strengthened user-centric design (lightweight smart materials for comfort, extended battery life) will boost long-term wearability,^{72,29} while targeted health education will empower users and foster a proactive health culture.^{2,61}

In summary, Figure 6's three-phase timeline clarifies wearable AI's phased goals and development roadmap.^{25,75} From 2026 core technology integration, to 2028 therapeutic device clinical application, and 2030 mature ecosystem construction, wearable AI will shift from "data collection" to "action guidance"

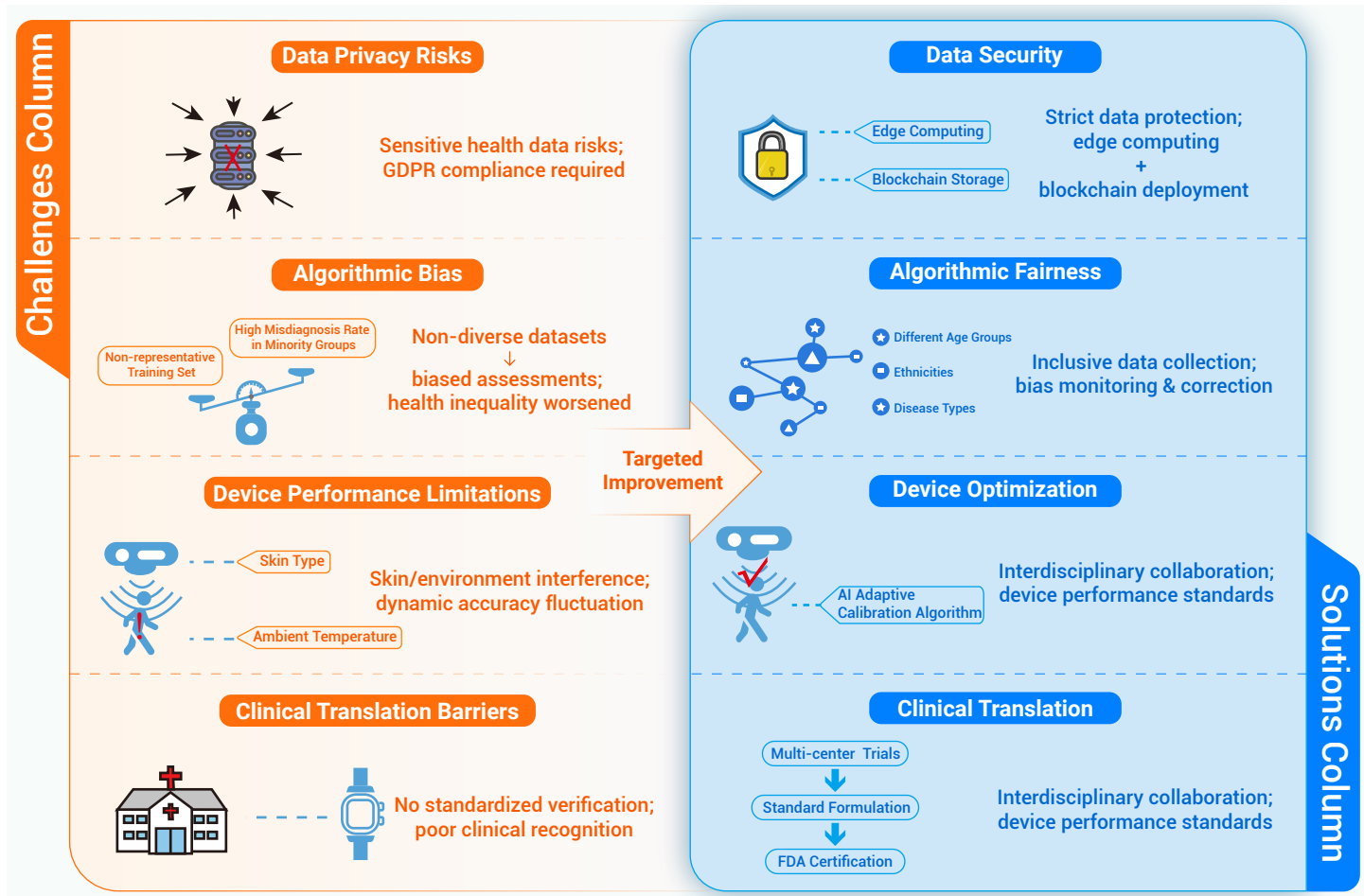


Figure 5. Two-column comparison schematic of core challenges and solutions for wearable AI technology Caption: This figure presents a two-column comparative schematic, systematically mapping core challenges of wearable AI technology (left column) to targeted solutions (right column). Challenges include sensor accuracy interference, edge computing constraints, algorithmic bias, poor user acceptance, and regulatory compliance gaps. Corresponding solutions encompass multimodal sensor fusion, lightweight AI models, inclusive data collection, material science advancements, and cross-stakeholder regulatory collaboration. Adapted from.⁶⁸

and from "individual monitoring" to "systematic management". Advancing smart materials, edge computing, AI, plus improved clinical translation and regulatory systems, will make wearable AI increasingly critical to proactive health management, ultimately building a more precise, efficient and patient-centric healthcare model.^{59,61}

CONCLUSION

The emergence of wearable artificial intelligence (AI) devices has triggered a transformative shift in proactive health management, unlocking remarkable potential across cardiovascular monitoring, metabolic disease diagnosis, respiratory health tracking, mental health assessment, and beyond. These technologies are not mere supplements to traditional healthcare practices but redefine the paradigm of modern health management—empowering individuals to take charge of their well-being while enabling healthcare systems to shift from reactive treatment to preventive care.

AI technology trends shaping the field

Three core technological trends are driving the advancement of wearable AI in proactive health management. First, multimodal data fusion—integrating physiological signals (e.g., ECG), bodily fluid biomarkers (e.g., sweat electrolytes), and behavioral data (e.g., activity patterns)—enables a holistic and precise health assessment that surpasses single-dimensional monitoring. Second, edge computing integration reduces reliance on cloud-based processing, enabling real-time data analysis directly on devices. This not only enhances response speed for time-sensitive health alerts but also mitigates privacy risks by minimizing data transmission. Third, adaptive AI algorithms—powered by deep learning and reinforcement learning—continuously optimize based on individual user data, refining disease prediction

accuracy and personalizing health recommendations to match unique physiological characteristics and lifestyle patterns.

Persistent challenges to overcome

Despite significant progress, the field faces three critical challenges that hinder widespread adoption and clinical translation. First, data quality and standardization remain foundational barriers. The accuracy of wearable sensors varies across environments and user groups, while the lack of unified data formats complicates cross-device integration and clinical validation. Second, privacy, security, and algorithmic transparency pose ethical and practical dilemmas. The collection of sensitive health data demands robust encryption and governance frameworks to prevent breaches, while opaque "black-box" algorithms undermine trust among users and healthcare providers. Third, clinical translation and accessibility gaps persist. Many innovative devices remain confined to research settings, lacking rigorous clinical trials to prove efficacy, and cost barriers or limited digital literacy exclude underserved populations from accessing these technologies.

Future outlook for proactive health management

The future of wearable AI in proactive health management is poised to evolve toward a more intelligent, integrated, and equitable ecosystem. Technologically, advancements in smart materials (e.g., flexible, biocompatible sensors) and microfluidic technology will lead to more unobtrusive, long-wearing devices capable of real-time, multiplexed biomarker detection. Clinically, wearable AI will increasingly integrate with electronic health records (EHRs) and telemedicine platforms, enabling seamless data sharing between users and healthcare providers to support timely, data-driven clinical decisions. At a systemic level, the establishment of unified technical standards,

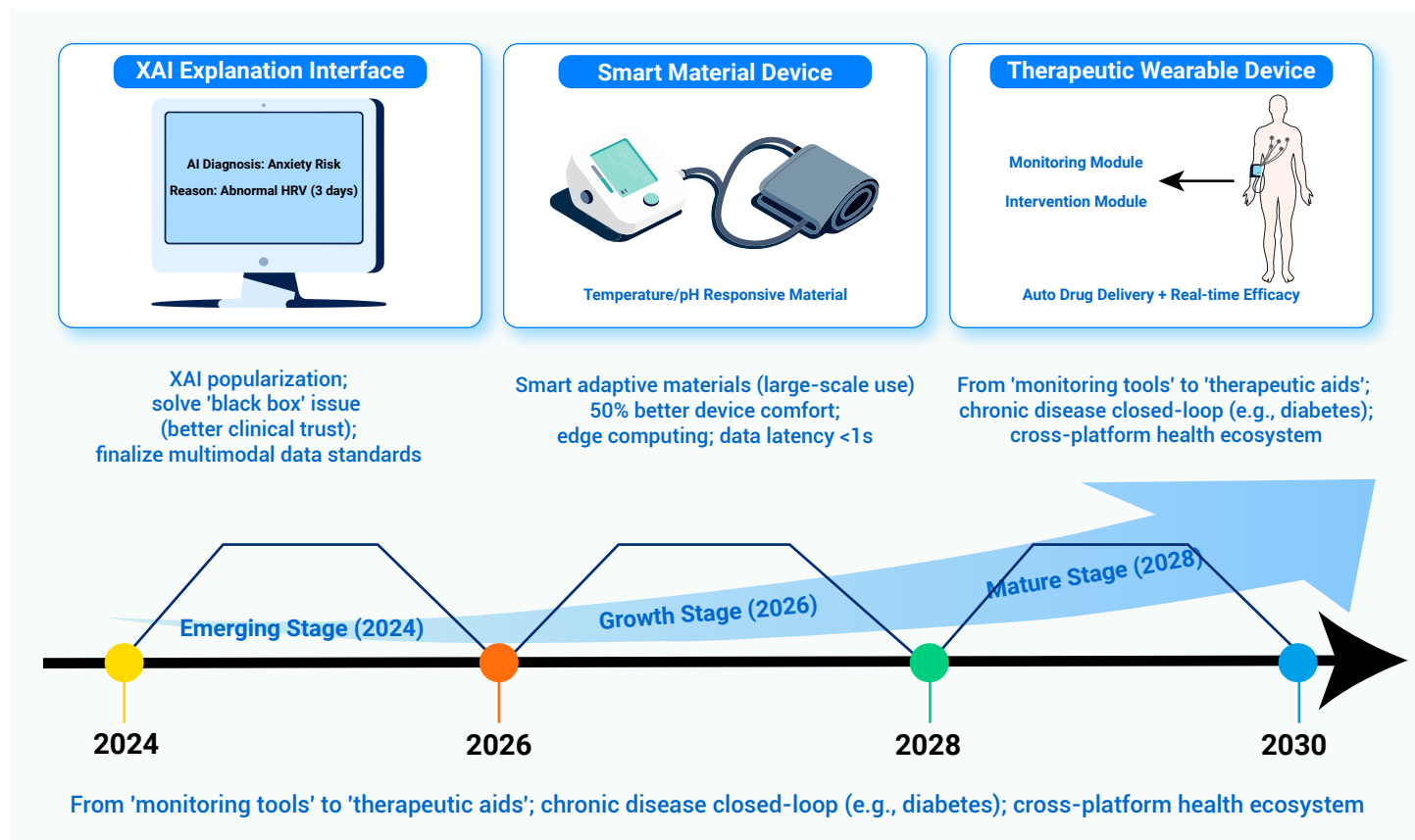


Figure 6. 2024-2030 technology development timeline.

privacy regulations, and reimbursement policies will facilitate the integration of wearable AI into standard healthcare workflows. Ultimately, these advancements will foster a patient-centered intelligent health ecosystem—one where care is tailored to individual needs, health risks are identified and addressed early, and healthcare resources are allocated more efficiently. This will not only improve individual health outcomes but also contribute to building a more equitable, sustainable, and proactive global healthcare system.

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FUNDING AND ACKNOWLEDGMENTS

This work was supported by the Foundation of the Shanghai Municipal Education Commission (No.24RGZNA05) and the National Natural Science Foundation of China (Grant No. 82273585). The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

AUTHOR CONTRIBUTIONS

G.F.L.: writing—original draft, visualization, methodology, software, data curation. W.J.M: resources, funding acquisition. H.D.Z: supervision. Y.Y.Z.: methodology. Y.H.Z:

methodology, conceptualization, data curation, resources, project administration, supervision, funding acquisition. All authors contributed to and approved the manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

DATA AND CODE AVAILABILITY

Not applicable.