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AI-Powered Wearable Sensors for Health Monitoring and Clinical Decision Making

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Abstract

AI-powered wearable sensors are transforming remote health monitoring by enabling real-time diagnostics, personalized interventions and proactive disease management. This review synthesizes recent advances in AI-integrated biosensors across conditions such as diabetes, cardiovascular disease, neurodegenerative dis- orders, mental health, and maternal/neonatal care, while addressing challenges of scalability, privacy, interoperability, and model robustness. We highlight machine learning methods—including federated learning, transfer learning, and edge- AI—that enhance the processing of physiological signals i.e., glucose levels, gait patterns, and heart rate variability. Key innovations, including FDA-approved glucose monitors and digital twins for predictive health modeling, underscore the shift toward patient-centric and data-driven care. Yet, persistent gaps remain, including device heterogeneity, privacy concerns, and the need for adaptive models that generalize across populations. Emerging approaches such as large language models and counterfactual explanations provide contextualized insights and transparent decision-making. By bridging technical advances with clinical needs, this review charts a roadmap toward democratized, equitable, and precise healthcare.

Keywords: digital twin; counterfactual; wearable sensor; mobile health; personalized health monitoring; LLM; hydration; glucose monitor; stress; behavioral health; deep learning; human-in-the-loop; real-time monitor; Parkinson; gait

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1. Introduction

Wearable sensors and embedded systems have demonstrated potential to revolution- ize the way healthcare is delivered, enabling continuous monitoring of physiological parameters outside of traditional clinical settings. These technologies are becoming integral in a wide range of applications, including disease diagnosis, chronic disease management, disease prevention, fitness tracking, and personalized health interven- tions [1,2]. Central to this transformation is the integration of Artificial Intelligence (AI) with biosensors, which enhances the capabilities of wearable devices by enabling real-time data analysis, pattern recognition, and predictive modeling.

AI-powered biosensors are equipped with advanced algorithms that can process data directly from the sensor to provide actionable insights, detect anomalies, and predict health events in real-time [3]. This paradigm shift has the potential to not only improve the accuracy and efficiency of health monitoring but also contribute to personalized medicine by adapting to individual needs and preferences [4]. With the increasing availability of data and the rise of machine learning techniques, AI has become an indispensable tool in enhancing the functionality and usability of wearable sensors.

However, the application of AI in wearable sensors presents unique challenges. These include ensuring model robustness in the presence of distribution shifts, where sensor data can vary across different environments and populations, and developing personalized models that can adapt to individual users over time [5,6]. Further- more, the integration of edge AI and human-in-the-loop

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systems adds another layer of complexity, requiring seamless interaction between the device and its user to refine predictions based on user feedback.

This review explores the latest developments in AI-powered wearable biosensors and bio instrumentation, focusing on key advancements, challenges, and future direc- tions in this rapidly evolving field. We will examine how AI is being used to address issues related to model personalization, robustness, and edge computing, as well as how human feedback can further optimize system performance and user experience.

2. Materials and Methods

2.1. Study Design

This scoping review was conducted following the guidelines of the Preferred Report- ing Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) [7], a framework that standardizes reporting to improve transparency and comprehensiveness in scoping reviews. Unlike systematic reviews, which focus on narrowly defined clinical questions, scoping reviews aim to map the breadth of litera- ture, identify key concepts, methodologies, and evidence gaps, and clarify definitions in emerging fields. Figure 1 provides an overview of the screening process, detailing the number of records identified, screened, and included in the final synthesis. These guide- lines provided a structured approach to ensure the review's comprehensiveness and rigor, focusing on the integration of AI-powered biosensors in wearable devices across diverse health applications.

2.2. Eligibility Criteria

For this review, we included peer-reviewed articles that explored the application of AI-powered wearable biosensors in health monitoring, diagnostics, and personalized medicine. Eligible studies were required to demonstrate empirical findings, providing quantitative or qualitative insights into the performance, efficacy, and challenges of these technologies. Articles had to be published within the last decade (January 1, 2014 to December 31, 2024) to reflect advancements in AI and wearable biosensor technologies and written in English to ensure accessibility and thorough analysis.

While the focus of the synthesis was on empirical studies, we also included selected review papers and methodological guidelines when they provided essential context, broader perspectives, or state-of-the-art summaries relevant to AI-powered biosen- sors. Commentaries, theoretical models without empirical or technical evaluation, and studies outside the timeframe remained excluded.

The timeframe of 2014 onwards was chosen as a critical starting point due to the rapid evolution of AI applications in wearables during this period, driven by advance- ments in edge computing, federated learning, and biosensor miniaturization. This window ensures a comprehensive examination of the field's recent developments and trends.

2.3. Information Sources

Relevant studies were identified by conducting systematic searches across major elec- tronic databases, including PubMed, Scopus, IEEE Xplore, and Web of Science. The search strategy employed a combination of keywords and Boolean operators to ensure the retrieval of relevant studies. Keywords included "AI-powered biosensors," "wear- able technology," "health monitoring," "real-time diagnostics," and "personalized medicine." Database searches were completed on November 15, 2024.

2.4. Search and Selection of Sources of Evidence

A standardized data extraction protocol was developed to ensure consistency and accuracy in capturing relevant information from the included studies. Key data points included publication details (authors, year), study location, sample size, sensor types and configurations, AI methodologies, health domains addressed, and main outcomes. Data extraction was independently

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conducted by two reviewers to minimize bias and improve reliability. Any discrepancies were resolved through discussion or consultation with a third reviewer.

To address the study's objectives, the research question was framed using the PICO (Population, Intervention, Comparison, Outcome) framework [8]. The popula- tion included users of wearable biosensors, the intervention focused on AI-powered biosensor applications, and the outcomes centered on advancements in health mon- itoring, personalization, and diagnostic accuracy. Search terms such as "AI-powered biosensors", "wearable health monitoring", "edge AI in wearables", and "personalized health diagnostics" were employed to identify studies showcasing the role of biosensors in dynamic and real-time health monitoring scenarios. The review aimed to synthesize findings on how wearable biosensors combined with AI enhance user safety, opti- mize health interventions, and address issues like privacy, personalization, and model robustness.

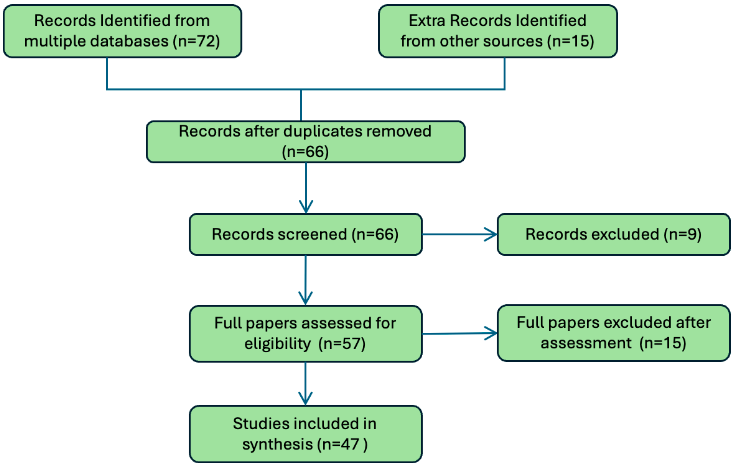

Figure 1. PRISMA Flow Diagram for Study Selection Process.

Table 1. Characteristics of Included Studies.

Study(Year)	Sample Size /Setting	Sensor(s)	AI Method	Domain	Outcome	External Validation
[9](2023)	Review (100+ studies)	ECG, PPG, EMG	ML/DL	General health	Overview of AI wearables	No
[10](2024)	4 public datasets	HR, sleep, metabolic	LLMs	Mental, metabolic, sleep	HealthAlpaca SOTA	Yes
[11](20224)	26	IMUs	Transformer	Parkinson's FoG	Reduced false posi- tives	Yes
[12](2025)	Field study in workers	Sweat sensor	Regression	Hydration	Real-time sodium alerts	Yes

3. Recent Advancements in Mobile Health

With AI systems getting more and more powerful, in the recent days, mobile health has become an integral part of our daily lives, even without always realizing it. About 21% of American adults wear smartwatches according to a 2019 consumer report (source: Statista [13]). Recent advancements in wearables and smartwatches have significantly enhanced their capabilities, transforming them into powerful tools for health monitor- ing, fitness tracking, and beyond [14]. Modern devices integrate cutting-edge sensors that measure vital signs such as heart rate, blood oxygen levels, and even electrocar- diograms (ECGs) with clinical-grade accuracy [15]. Innovations in artificial intelligence and machine learning allow these wearables to provide personalized insights, detect anomalies like

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arrhythmias, and predict health trends over time [9]. Additionally, wearable ecosystems now include stress monitoring, sleep quality assessment, and men- strual health tracking, catering to diverse user needs [16–18]. With longer battery life, improved water resistance, and sleek designs, wearables are becoming indispensable in daily life. Continuous Glucose Monitors (CGMs) are revolutionizing diabetes manage- ment by offering real-time insights into glucose levels without the need for fingerstick tests. These wearable devices use tiny sensors inserted under the skin to measure inter- stitial glucose levels, enabling users to track fluctuations and trends throughout the day and night. Advanced CGMs provide predictive alerts for high or low glucose levels and integrate seamlessly with smartphones, insulin pumps, and health apps, empow- ering users to make data-driven decisions. A significant milestone in their adoption is the recent FDA approval of certain CGMs for over-the-counter sales, making them more accessible to individuals with diabetes or those looking to monitor their glucose for general health purposes [19]. This shift highlights the growing recognition of CGMs as essential tools for proactive health monitoring, promoting broader usage beyond clinical settings.

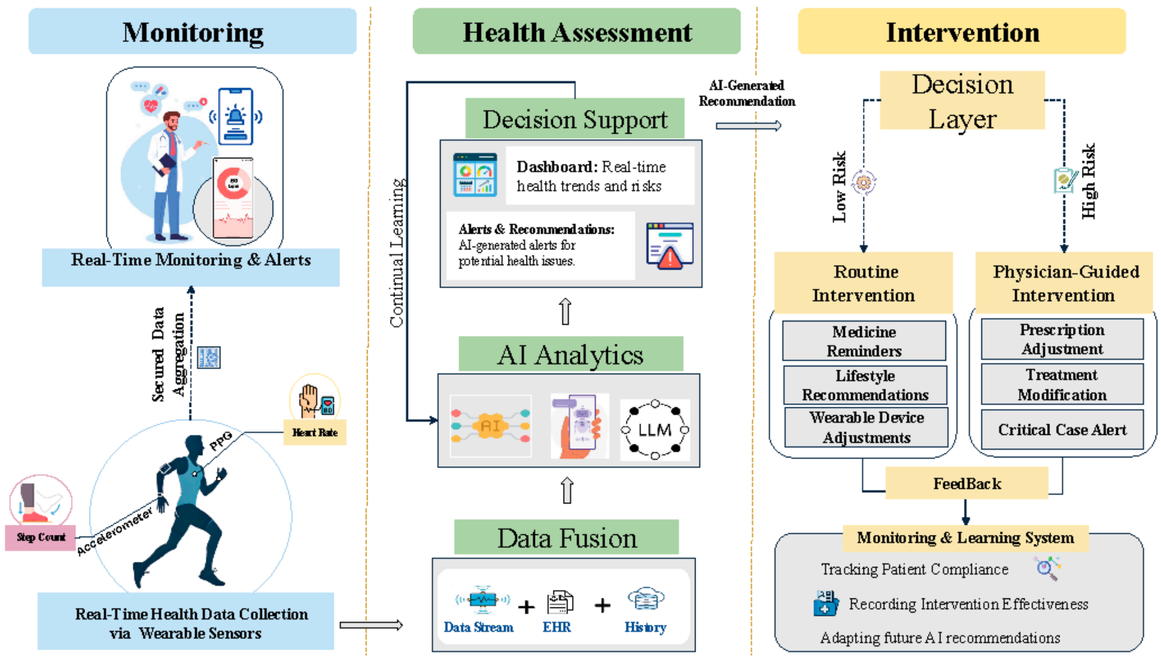

Figure 2. A Conceptual Framework for Intelligent Health Monitoring and Adaptive Interventions.

Figure 2 provides a conceptual overview of AI-powered wearable biosensors and their role in healthcare. The framework is structured into three pillars: monitoring, health assessment, and intervention. The monitoring pillar captures real-time physiologi- cal and behavioral data through wearable and implantable biosensors, which is then processed using AI-driven algorithms. The health assessment pillar enables pattern recognition, anomaly detection, and predictive modeling, incorporating techniques like federated learning, transfer learning, and continual learning to enhance model robust- ness. Finally, the intervention pillar translates AI-driven insights into personalized health recommendations, clinical decision support, and adaptive interventions. This modular approach illustrates how AI, human-in-the-loop systems, and digital twin technologies work together to optimize personalized medicine and real-time health monitoring (Figure 2).

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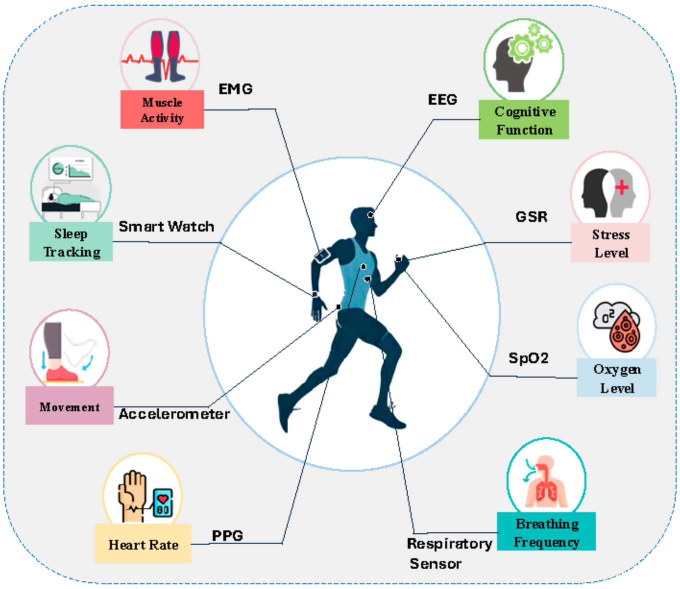

Figure 3. Applications of Wearable Biosensors for Real-Time Health Monitoring. Illustrated signals include EMG (electromyography) for muscle activity, EEG (electroencephalography) for cognition and brain activity, PPG (photoplethysmography) for heart rate/vascular health and *SpO*2 (pulse oximetry) for oxygen saturation.

4. Applications of Biosensors

Wearable biosensors have become essential tools for continuous health monitoring, enabling the measurement of multiple physiological and behavioral parameters. Figure 3 illustratesthese applications, while Table 2 provides a categorized overview of health conditions where biosensors are most widely applied. These include physiological and behavioral health monitoring, gait and motor function, neurodegenerative diseases, metabolic and hydration health, and maternal/neonatal care.

4.1. Metabolic and Neonatal Health

In recent years biosensors have become transformative tools in metabolic health, where they are extensively used to manage conditions such as diabetes and obesity. CGMs provide real-time insights into glucose fluctuations, enabling better glycemic control and early detection of irregularities. Recent work shows that LLM-based counter- factual generation (e.g., GPT-4o-mini) can enhance explainability and robustness in metabolic health prediction tasks [42,43]. Beyond diabetes, biosensors are being used to monitor metabolic biomarkers like lactate and ketones, aiding in personalized diet and exercise regimens [9].

Table 2. Applications of Biosensors in Health Conditions.

Application	Publications
Physiological and Behavioral Mental Health Monitoring (Sleep, Stress, Anxiety, Cardiovascular, Substance Use Monitoring)	[1,10,15,16,18,20–24]
Gait and Motor Function Monitoring	[11,25–28]
Neurodegenerative Chronic Diseases (Parkinson, Alzheimer)	[11,25,26]
Obesity, Metabolic, Hydration Health	[9,10,12,29–34]
Maternal / Neonatal / Women's Health	[17,35–37]

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Table 3. The methodologies used in biosensors and their associated physiological signals or biomarkers.

Methodology	Signals/Biomarkers	Publications
Human Activity Recognition (HAR) & Behavioral Health	Motion sensors, accelerometers, gyroscopes, heart rate	[10,27,38–41]
Gait/Motor Function Analysis	Gait speed, step frequency, movement symmetry, Irregular biometric signals, deviations in heart rate, temperature, movement patterns	[11,25–27]
Glucose (CGMs), Hydration Monitoring	Blood glucose levels, metabolic biomarkers, Fluid intake volume, type of liquid consumed	[9,12,30,31]

In neonatal health, biosensors are deployed to monitor vital parameters such as oxygen saturation, heart rate, and respiration in real-time, providing critical sup- port in neonatal intensive care units (NICUs). These devices can alert clinicians to potential adverse events, such as hypoxia or bradycardia, ensuring timely interven- tions and better outcomes for premature or at-risk infants [17]. Integrating AI with biosensors further enhances their utility, enabling predictive analytics and personalized recommendations in these domains.

4.2. Cardiovascular Health

In cardiovascular health, biosensors play a pivotal role in monitoring heart rate, blood pressure, and other hemodynamic parameters, aiding in the early detection of arrhyth- mias, hypertension, and heart failure. Devices such as smartwatches, ECG patches, and chest straps enable continuous and non-invasive monitoring, empowering individuals to manage their cardiovascular health proactively. AI-driven algorithms strengthen these applications by detecting anomalies and predicting adverse events, thereby empower- ing individuals to manage their cardiovascular health more proactively [15,23].

Table 4. Key Challenges in Integrating Wearable Electronics with Biological Systems.

	Biology	Wearable Electronics
Mechanical Properties	Flexible, soft, and compliant organic materials	Stiff, brittle, and rigid inorganic struc- tures
Fabrication Techniques	3D self-organized growth and assembly	2D structured patterns using litho- graphic methods
Operational Environment	Hydrated, dynamic, and biochemical surroundings	Dry, static, and controlled conditions
Functional Principles	Predominantly ion-driven processes with genetic regulation	Primarily electron-driven systems gov- erned by electromagnetic theory

4.3. Neurological and Cognitive Health

Biosensors are also transforming neurological and cognitive health monitoring, espe- cially in chronic disorders such as Parkinson’s and Alzheimer’s diseases. In Parkinson’s disease, wearable sensors can capture motor symptoms such as tremors, gait abnor- malities, and freezing of gait [44], supporting both early diagnosis and therapy adjustments [11,26]. In Alzheimer’s care, biosensors are used to monitor sleep patterns, cognitive function, and physiological stress markers, offering insights into disease pro- gression and the effectiveness of interventions. Table 3 complements this by outlining the main methodologies and corresponding biomarkers that enable these applications.

5. Challenges with AI-Powered Biosensors

AI-powered biosensors, widely used for health monitoring and diagnostics, often face challenges related to data privacy, personalization, and model robustness. Traditional centralized learning methods require aggregating user data in a single location, rais- ing significant privacy and

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security concerns. Federated learning is a decentralized approach in which models are trained locally on users' devices and only model updates (not raw data) are shared. This addresses this by enabling biosensors to collabora- tively train AI models locally on their devices, ensuring sensitive health data remains private. Edge-AI- the deployment of AI algorithms directly on local devices such as smartphones, wearables, and IoT sensors-transforms how data is processed and uti- lized. By performing computations locally on the device rather than relying on cloud servers, Edge-AI minimizes latency, enhances data privacy, and reduces the band- width needed for data transmission. This is particularly beneficial for time-sensitive applications like health monitoring with biosensors, autonomous vehicles, and real- time industrial automation [45]. Edge-AI systems leverage specialized hardware such as AI accelerators and optimized algorithms to ensure efficient performance within the resource constraints of edge devices. Moreover, the technology supports offline func- tionality, enabling critical operations even in areas with poor connectivity. As Edge-AI continues to evolve, advancements in energy-efficient neural networks and federated learning further enhance its potential, making it a cornerstone for next-generation AI applications across diverse industries [44].

Another common issue is the heterogeneity of biosensor devices, such as differ- ences in sensor quality, user behaviors, and environmental conditions. Transfer learning can mitigate these issues by leveraging pre-trained models to adapt quickly to new devices or scenarios, reducing the need for extensive retraining. Moreover, biosensors frequently deal with noisy, incomplete, or imbalanced datasets, which can impair AI performance, especially in detecting rare but critical health conditions [25,38,39].

Continual learning and human-in-the-loop systems are pivotal in addressing chal- lenges associated with adaptability and interpretability. Biosensors operate in dynamic environments where users' physiological patterns may change due to aging, illness, or lifestyle adjustments, requiring models to adapt continuously without catastrophic forgetting of prior knowledge. Continual learning enables this by allowing mod- els to incrementally learn from new data while retaining previous knowledge [27]. Human-in-the-loop systems further enhance the reliability of AI-powered biosensors by incorporating user feedback and expert annotations. These systems help correct errors, refine predictions, and improve user trust in the technology. By combining federated learning, continual learning, transfer learning, and human-in-the-loop approaches, AI- powered biosensors can overcome critical challenges, paving the way for more robust, personalized, and secure health monitoring solutions.

Despite advancements in AI-powered biosensors, fundamental differences between biological systems and wearable electronics pose additional challenges. Biology and electronics differ significantly in their materials, functional principles, fabrication tech- niques, and operational environments, creating a complex interface for integration. For instance, biological systems are inherently flexible, soft, and dynamic, whereas wearable electronics are often rigid, brittle, and optimized for static conditions. These differences, summarized in Table 4, highlight the need for innovative design approaches to bridge the gap between biological and electronic systems effectively.

In addition to technical hurdles, regulatory and reimbursement barriers remain major obstacles. The regulatory landscape lacks unified standards for evaluating algo- rithmic fairness, safety, and efficacy, and agencies such as the FDA require rigorous clinical evidence and explainability before approval [46]. On the reimbursement side, fragmented payer policies and the absence of standardized codes create financial uncer- tainty and limit adoption, as insurers often demand costly, longitudinal evidence of improved outcomes before coverage. [47]

6. Future of AI-Powered Biosensors

The future of AI-powered biosensors lies in their integration with cutting-edge technologies like Large Language Models (LLMs), digital twins, and counterfactual explanations, enabling more intelligent and personalized healthcare solutions. One emerging area is precise diet and hydration recommendations, where biosensors can track fluid intake and optimize hydration levels in real-time.

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Hydration plays a vital role in both physical performance and cognitive health, yet current wearable technolo- gies lack the ability to monitor both fluid type and volume simultaneously [12,31]. LLMs can serve as a critical component of the biosensor ecosystem by processing and contextualizing vast amounts of health data. They can generate personalized health insights, offer recommendations based on user-specific patterns, and act as conver- sational agents for patients and clinicians. For instance, LLMs can synthesize data from wearables and biosensors to identify correlations between lifestyle factors and health metrics, guiding users in optimizing their behaviors [30?]. Moreover, their nat- ural language capabilities enable users to interact intuitively with health systems, ask questions about their data, and receive comprehensible explanations, bridging the gap between complex AI outputs and human understanding [10,48].

Digital twins and counterfactual explanations promise to revolutionize how biosen- sor data is analyzed and utilized. A digital twin is a computational model or virtual replica of an individual's physiological systems that continuously integrates real-time data from wearable sensors with historical and contextual health information. Unlike static models, digital twins are dynamic and adaptive, allowing them to simulate the effects of interventions such as medication adjustments, lifestyle changes, or exercise routines, and predict how these changes would impact health outcomes over time. Biosensors will feed real-time data into these digital twins, ensuring that the simu- lations are dynamic and accurately reflect the user's current health status [49,50]. Meanwhile, counterfactual explanations will enhance trust and transparency in AI- powered biosensors by illustrating alternative scenarios. For example, they can explain to users how changes in diet, exercise, or medication would affect health outcomes, offering actionable insights. Together, these innovations will empower individuals and healthcare providers with predictive, explainable, and actionable intelligence, advanc- ing precision medicine and preventative care. The convergence of these technologies ensures a future where AI-powered biosensors are not just tools for monitoring but also partners in health decision-making.

7. Conclusion

In summary, advancements in AI-powered technologies like wearables, CGMs, and biosensors are revolutionizing healthcare by enabling personalized, real-time monitor- ing and decision-making. The growing accessibility of devices, such as over-the-counter CGMs, underscores their expanding role beyond clinical settings, empowering individ- uals to take control of their health. However, these innovations come with challenges such as data privacy, device heterogeneity, and the need for robust, adaptable AI models. Techniques like federated learning, continual learning, transfer learning, and human-in-the-loop systems address these issues by enhancing privacy, adaptability, and reliability. Similarly, the rise of Edge-AI is driving efficiency and responsiveness by processing data locally on devices, ensuring real-time functionality even in constrained environments. Together, these advancements are shaping a future where AI-powered health technologies are more accessible, secure, and effective, paving the way for a smarter and healthier society.

Special and Outstanding Interest — Papers of special interest are highlighted with one asterisk (*) and those of outstanding interest with two asterisks (**). Annotated references were selected from the past two years to emphasize studies of particular novelty, methodological rigor, or significant impact in the field of AI-powered wearable biosensors.

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