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# Artificial Intelligence–Enabled Wearable Sensors for Continuous Health Monitoring-An Updated Review for Biomedical Engineering

**Mesfer Zaid Hathal Alkhamis (1) , Fahad Mohmmed Al Thafir (1) , Mohammed Abdullah Alskhabrah (1) , Mohammed Razqan Matar Almutairi (2) , Mohammed Fahad Bin Zayid (2) , Sultan Ghusayn Aldawsari (1) , Mohammed Mahdi Mufarrah Al-Kubra (1) , Mohammed Abdullah Al Suliman (1) , Mishal Rashid Al Juma (3) , Nasser Saeed Alwuhayyid , Zakaria Mohammed Al Muhaymid (1) , Alanoud Abdullah Alhulayyil (4) , Hessa Trad Alonzay (4)**

*(1) Al-Aflaj Hospital,Ministry of Health, Saudi Arabia,*
*(2) King Saud University, Saudi Arabia,*
*(3) Al-Aflaj General Hospital,Ministry of Health, Saudi Arabia,*
*(4) King Khalid Hospital – Al-Kharj,Ministry of Health, Saudi Arabia*

## Abstract

**Background:** Wearable biosensors integrated with artificial intelligence (AI) have significantly advanced continuous health monitoring by enabling real-time, personalized, and non-invasive assessment of physiological and behavioral parameters beyond traditional clinical environments. These technologies support disease management, early diagnosis, preventive care, and personalized interventions across diverse health domains.

**Aim:** This review aims to summarize recent advancements in AI-enabled wearable biosensors, focusing on their applications, methodological innovations, challenges, and future directions in biomedical engineering.

**Methods:** A comprehensive narrative review of recent scientific literature was conducted, analyzing developments in wearable sensor technologies, AI methodologies (including machine learning, deep learning, edge AI, federated learning, and human-in-the-loop systems), and their applications across metabolic, cardiovascular, neurological, and neonatal health domains.

**Results:** AI-powered wearable biosensors demonstrate high potential for continuous health monitoring, predictive analytics, and personalized intervention. Applications include glucose monitoring, cardiovascular risk detection, gait and motor assessment, and neonatal surveillance. Advances in edge computing and federated learning enhance privacy and real-time responsiveness, while digital twins and large language models improve interpretability and decision support.

**Conclusion:** AI-enabled wearable biosensors are transforming healthcare toward predictive, proactive, and personalized models of care, although challenges related to data privacy, robustness, biological integration, and regulation remain.

**Keywords:** Wearable biosensors; Artificial intelligence; Continuous health monitoring; Edge computing; Personalized medicine.

## Introduction

Wearable sensors and embedded systems are transforming healthcare by enabling continuous monitoring of physiological parameters beyond the confines of traditional clinical environments. These technologies provide real-time data collection in naturalistic settings, allowing healthcare providers and researchers to capture dynamic health trends that were previously difficult to observe. Applications of wearable sensors span disease diagnosis, chronic disease management, preventative healthcare, fitness tracking, and personalized health interventions, highlighting their versatility and growing relevance in modern healthcare delivery [1,2]. Their ability to continuously monitor vital signs, activity levels, and other biomarkers positions them as crucial tools for both clinical and non-clinical settings. A major innovation in this space is the integration of Artificial Intelligence (AI) with wearable biosensors. AI enhances the capabilities of these devices by enabling complex data analysis, pattern recognition, and predictive modeling in real time. Machine learning algorithms can process continuous streams of sensor data to detect anomalies, forecast potential health events, and generate actionable insights tailored to individual patients [3]. This integration has



*Corresponding author e-mail: mosfer1919@gmail.com (Mesfer Zaid Hathal Alkhamis).

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significant implications for personalized medicine, as AI-driven wearable devices can adapt to each user's unique physiological profile, lifestyle, and health history, offering tailored interventions and recommendations [4]. Such adaptability enhances the precision of monitoring, improves early detection of potential complications, and facilitates proactive healthcare management.

Despite their potential, AI-powered wearable sensors face significant challenges. One primary concern is model robustness, as sensor data can exhibit variability due to environmental factors, user behavior, or differences across populations, potentially impacting algorithmic performance [5]. Developing models that maintain accuracy under such distribution shifts is essential. Additionally, creating personalized models that adapt over time to individual users requires continuous learning capabilities and effective calibration strategies. The incorporation of edge AI—processing data locally on the device—and human-in-the-loop systems further complicates design, demanding seamless interaction between the device and the user to optimize predictions based on feedback [6]. Edge computing offers low-latency analysis and preserves data privacy, but it necessitates efficient algorithms capable of operating on limited hardware resources without compromising accuracy. This review examines recent advancements in AI-powered wearable biosensors and bioinstrumentation, focusing on innovations in model personalization, robustness, and edge computing. It explores how AI facilitates real-time analysis, anomaly detection, and predictive capabilities, and evaluates strategies to integrate human feedback to enhance system performance. Additionally, it addresses the broader implications of these technologies for clinical decision-making, patient engagement, and healthcare delivery. By synthesizing current developments, challenges, and future directions, this review highlights the transformative potential of AI-driven wearable sensors in enabling continuous, individualized, and predictive healthcare. The discussion underscores the importance of interdisciplinary collaboration between engineers, data scientists, and clinicians to design wearable systems that are both technologically sophisticated and clinically meaningful.

**Recent Advancements in Mobile Health**

The proliferation of artificial intelligence (AI) and mobile technologies has catalyzed a paradigm shift in healthcare, positioning mobile health (mHealth) as an integral component of daily life. Modern mHealth applications leverage wearable devices, smartwatches, and implantable biosensors to provide continuous monitoring of physiological parameters, facilitating real-time assessment of health status and enabling early detection of potential complications. Consumer adoption of these devices reflects their growing influence; for example, a 2019 report indicated that approximately 21 percent of American adults regularly use smartwatches, underscoring the mainstream integration of wearable technologies into personal health management [13]. Recent innovations in wearable devices have significantly enhanced their functionality. Advanced sensors now enable clinical-grade measurement of vital signs, including heart rate, blood oxygen saturation, and electrocardiograms (ECGs), offering unprecedented accuracy outside traditional clinical settings [14,15]. Integration of AI and machine learning has transformed these devices from passive data collectors into intelligent health assistants capable of analyzing longitudinal data, detecting anomalies such as arrhythmias, and predicting trends over time [9]. Beyond cardiovascular monitoring, wearables now encompass stress detection, sleep quality evaluation, menstrual health tracking, and physical activity assessment, reflecting a holistic approach to personal health management [16,17,18]. Improvements in device design, including extended battery life, water resistance, and ergonomics, further enhance usability and encourage consistent adoption.

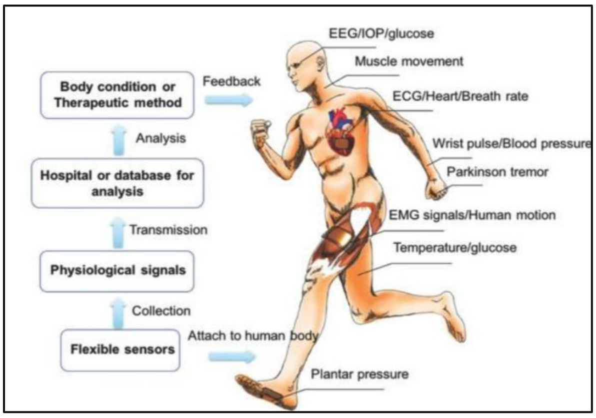


**Fig. 1:** AI-based Wearable Sensors.

A particularly notable advancement is the development and widespread adoption of Continuous Glucose Monitors (CGMs), which have redefined diabetes management. CGMs employ miniature sensors implanted subcutaneously to measure interstitial glucose levels continuously, eliminating the need for frequent fingerstick testing. The real-time monitoring capability allows users to track glucose fluctuations throughout the day and night, facilitating timely interventions and lifestyle adjustments. Advanced CGMs integrate predictive alerts for hypo- and hyperglycemia, enabling proactive management of glycemic levels. Additionally, seamless connectivity with smartphones, insulin pumps, and health applications empowers users to make informed, data-driven decisions. Regulatory recognition, including the U.S. Food and Drug Administration (FDA) approval of specific CGMs for over-the-counter sales, has increased accessibility, extending their utility beyond clinical populations to the general public [19]. This development exemplifies the transition of mHealth devices from therapeutic tools to preventive and wellness-oriented technologies. The operational framework of contemporary mHealth systems is often conceptualized around three pillars: monitoring, health assessment, and intervention. The monitoring pillar focuses on continuous acquisition of physiological and behavioral data through wearable and implantable biosensors. AI algorithms process these data streams in real time, enabling rapid detection of deviations from normative patterns. The health assessment pillar leverages advanced computational techniques, including federated learning, transfer learning, and continual learning, to recognize patterns, detect anomalies, and predict potential health events while maintaining model robustness across heterogeneous populations. This pillar emphasizes the adaptation of AI models to individual users, ensuring personalized and context-sensitive analysis.

The intervention pillar translates AI-generated insights into actionable strategies. These include personalized health recommendations, clinical decision support, and adaptive interventions tailored to the individual's needs. Integration of human-in-the-loop systems allows clinicians or patients to provide feedback that refines algorithmic predictions, while digital twin technologies create virtual representations of the user's physiological state to simulate interventions and predict outcomes. This synergistic approach ensures that mHealth platforms do not merely record data but actively contribute to health optimization and proactive management of chronic conditions. Collectively, these advancements illustrate the transformative potential of AI-driven mHealth technologies. By enabling continuous, personalized, and predictive health monitoring, wearables and biosensors bridge the gap between clinical care and everyday life. They empower users to make informed decisions, facilitate early intervention, and reduce the burden on healthcare systems by promoting preventive care. As sensor technology, AI methodologies, and data integration techniques continue to evolve, mHealth is poised to become an essential component of precision medicine, offering scalable solutions for individualized health management and improved clinical outcomes. The integration of AI, advanced sensors, and wearable technology exemplifies a shift from episodic, reactive care toward continuous, proactive, and personalized healthcare delivery. This trajectory emphasizes the role of real-time data acquisition, predictive analytics, and adaptive interventions in promoting population health, reducing disease burden, and enhancing patient engagement, highlighting the transformative role of mobile health in the future of medicine.

**Applications of Biosensors**

Wearable biosensors have emerged as transformative tools in healthcare, enabling continuous and non-invasive monitoring of physiological, behavioral, and biochemical parameters. Their integration into mobile and wearable platforms has created opportunities for real-time health assessment and personalized intervention, bridging the gap between traditional episodic clinical visits and continuous patient-centered care. Modern biosensors are capable of measuring a wide array of signals, including cardiac activity, blood oxygen saturation, electroencephalography (EEG), electromyography (EMG), galvanic skin response, glucose levels, hydration status, and motion parameters, among others. These capabilities allow for comprehensive monitoring across multiple domains of health and wellness. By capturing continuous longitudinal data, biosensors provide clinicians and researchers with insights into trends, anomalies, and early indicators of disease progression or deterioration, facilitating timely and precise intervention. Physiological and behavioral health monitoring is among the most extensively studied applications of wearable biosensors. Devices equipped with electrocardiogram (ECG), photoplethysmography (PPG), and other cardiac sensors can detect heart rate variability, arrhythmias, and cardiovascular anomalies with high sensitivity and specificity [9]. Machine learning (ML) and deep learning (DL) algorithms applied to these data streams enable early detection of cardiovascular events and behavioral stress indicators, while also providing feedback for lifestyle interventions [10,15].

Sleep and stress monitoring are also enhanced through wearable sensors that capture heart rate, movement, and skin conductance, allowing for comprehensive assessment of sleep quality, circadian rhythms, and stress-related physiological responses [16,18,20]. Biosensors integrated with substance use monitoring further expand the capability for behavioral intervention, providing real-time feedback for individuals in recovery or under medical supervision [21,22,23,24].

Gait and motor function monitoring represents another critical domain for biosensor applications. Inertial measurement units (IMUs) and accelerometers enable precise tracking of movement patterns, posture, and step dynamics. Studies have demonstrated that transformer-based AI models applied to IMU data can significantly reduce false positives in gait irregularity detection, particularly in Parkinson's disease patients experiencing freezing of gait (FoG) episodes [11,25,26]. Such systems provide both quantitative assessment for clinicians and real-time alerts for patients, improving mobility management and reducing the risk of falls. Continuous monitoring of motor function also facilitates rehabilitation and therapeutic evaluation, allowing interventions to be tailored to individual progress. Neurodegenerative chronic diseases, including Parkinson's and Alzheimer's disease, are another area where biosensors demonstrate substantial utility. By capturing motion, electrophysiological, and behavioral data, wearables can provide early markers of disease onset, track symptom progression, and monitor treatment efficacy [11,25,26,27]. AI-driven analytics applied to biosensor data allow for detection of subtle changes in motor function, cognitive performance, or physiological responses, supporting both clinical decision-making and research into disease-modifying therapies. Continuous and non-invasive monitoring is particularly valuable in neurodegenerative conditions where symptoms can fluctuate, and early intervention significantly impacts patient quality of life. Obesity, metabolic disorders, and hydration health constitute a rapidly expanding application domain for biosensors. Continuous glucose monitors (CGMs), sweat sensors, and multi-parameter metabolic sensors provide insights into glucose levels, electrolyte balance, and metabolic responses in real time [9,10,12,29,30,31]. AI-powered predictive models allow for trend analysis, early warning of hypo- or hyperglycemia, and guidance for dietary or pharmacological interventions. Field studies among workers using sweat sensors with regression-based AI models have demonstrated the capability for real-time sodium alerts, improving hydration management and reducing risks of heat-related illness [12]. Similarly, wearable devices for weight management and metabolic monitoring facilitate lifestyle interventions, adherence tracking, and long-term health outcomes.

Maternal, neonatal, and women's health also benefit from wearable biosensors. Devices capable of tracking fetal heart rate, maternal blood pressure, and uterine activity provide early detection of complications, support prenatal care, and improve neonatal outcomes [17,35,36,37]. Wearable technologies in this context allow for home monitoring, reducing the need for frequent hospital visits while maintaining clinical oversight. Integration with AI facilitates individualized recommendations and predictive alerts, ensuring both maternal and neonatal safety. Overall, wearable biosensors have transformed health monitoring across multiple domains by combining continuous data acquisition, AI-driven analysis, and personalized intervention. They provide actionable insights into physiological and behavioral health, motor function, neurodegenerative disease management, metabolic and hydration status, and maternal and neonatal care. Studies spanning public datasets, field trials, and clinical observations confirm the accuracy, usability, and potential of these devices in real-world settings [9,10,11,12]. As AI algorithms and sensor technologies continue to advance, biosensors are poised to become even more integral to personalized healthcare, preventive medicine, and clinical decision-making, highlighting their critical role in the future of biomedical engineering and digital health.

**Metabolic and Neonatal Health**

Wearable biosensors have emerged as transformative tools in metabolic health, enabling continuous, personalized monitoring of physiological and biochemical parameters. In recent years, their application has expanded significantly in the management of chronic metabolic conditions such as diabetes, obesity, and electrolyte imbalances. Continuous glucose monitors (CGMs) represent one of the most established applications of biosensors in metabolic health. By providing real-time data on interstitial glucose concentrations, CGMs allow individuals and clinicians to track glucose fluctuations throughout the day and night, facilitating more accurate insulin dosing, dietary adjustments, and activity management. This real-time feedback has been shown to improve glycemic control, reduce episodes of hypoglycemia, and support better long-term outcomes in both Type 1 and Type 2 diabetes [9]. Advances in artificial intelligence (AI) have further augmented the utility of metabolic biosensors. Machine learning and deep learning algorithms can analyze large, continuous datasets from CGMs and other metabolic sensors to identify trends, predict glucose excursions, and generate actionable recommendations. Recent work has demonstrated that large language model (LLM)-based counterfactual generation, for instance using models like GPT-4o-mini, can improve explainability and robustness in metabolic health prediction tasks [42,43]. By generating interpretable scenarios and highlighting potential deviations from predicted trajectories, LLMs enhance patient understanding and clinician trust in AI-driven recommendations. Beyond glucose, biosensors are increasingly used to monitor other metabolic biomarkers, including lactate, ketone bodies, and electrolyte concentrations. These measurements support personalized interventions in diet, exercise, and hydration management, enabling precision medicine approaches for obesity, metabolic syndrome, and athletic performance optimization [9]. In neonatal health, biosensors provide critical support in monitoring the fragile physiology of newborns, particularly those admitted to neonatal intensive care units (NICUs). Continuous monitoring of vital signs such as heart rate, oxygen saturation, and respiration is essential for early detection of hypoxia, bradycardia, apnea, or other adverse events. Traditional intermittent monitoring methods often miss transient episodes of instability, whereas wearable and embedded biosensors allow uninterrupted assessment, alerting clinicians to immediate risks and enabling timely intervention [17]. These devices also facilitate long-term monitoring of growth parameters and metabolic status in premature or at-risk infants, reducing the likelihood of complications and supporting individualized care plans. Integration of AI in neonatal biosensors enables predictive analytics, where subtle trends in physiological data can indicate impending deterioration, guiding preemptive clinical action. AI-driven models can also assist in optimizing ventilator settings, fluid administration, and other therapeutic interventions by analyzing continuous multimodal data streams from biosensors.

**Cardiovascular Health**

In cardiovascular health, wearable biosensors have become essential for proactive monitoring and early detection of pathophysiological changes. Devices such as smartwatches, ECG patches, chest straps, and photoplethysmography (PPG)-enabled sensors allow continuous, non-invasive tracking of heart rate, blood pressure, oxygen saturation, and other hemodynamic parameters. These data streams provide insights into the cardiovascular system’s status in real time, supporting early identification of arrhythmias, hypertension, and signs of heart failure [15,23]. AI-enhanced wearable systems apply advanced algorithms to detect anomalies, predict adverse events, and provide users with personalized feedback for lifestyle modifications or medical interventions. Continuous monitoring empowers patients to engage actively in their cardiovascular health management, reducing hospitalizations, and enabling clinicians to intervene before complications escalate. Predictive models built on longitudinal cardiovascular data also enable stratification of patient risk, supporting tailored care plans and enhancing precision medicine initiatives.

**Neurological and Cognitive Health**

Biosensors are revolutionizing neurological and cognitive health monitoring, particularly in chronic neurodegenerative disorders. In Parkinson’s disease, wearable sensors equipped with accelerometers, gyroscopes, and inertial measurement units (IMUs) capture motor symptoms such as tremors, rigidity, bradykinesia, and freezing of gait (FoG) episodes [11,26,44]. The continuous capture of motion data allows clinicians to track disease progression, assess therapeutic efficacy, and adjust medication schedules with higher precision than traditional clinic-based assessments. AI algorithms applied to these datasets reduce false-positive detections, identify patterns of deterioration, and provide real-time alerts for patients at risk of falls. In Alzheimer’s disease and other cognitive disorders, biosensors facilitate monitoring of sleep patterns, activity levels, physiological stress markers, and cognitive engagement. Changes in these parameters can provide early indicators of disease progression, guide intervention strategies, and enable evaluation of treatment efficacy. For instance, heart rate variability, electrodermal activity, and movement patterns tracked via wearable sensors provide objective measures of stress, agitation, and sleep quality, which are critical for patients with cognitive impairments. Integration of AI enables the synthesis of these multimodal datasets into actionable insights for both caregivers and clinicians, improving patient safety and quality of life.

**Methodologies and Biomarkers**

Biosensor applications rely on diverse methodologies to capture physiological and behavioral signals, translating them into meaningful health insights. Table 3 summarizes the primary methodologies and their associated biomarkers. Human activity recognition (HAR) employs motion sensors, accelerometers, gyroscopes, and heart rate data to monitor general behavior, sleep, and stress levels [10,27,38,39,40,41]. Gait and motor function analysis utilizes step frequency, movement symmetry, and irregular biometric signals to detect deviations associated with neurological disorders [11,25,26,27]. Continuous glucose monitoring and hydration assessment involve direct measurement of blood glucose levels, lactate, ketones, and fluid intake metrics, supporting metabolic health interventions [9,12,30,31]. Collectively, these methodologies demonstrate the breadth of biosensor applications across health domains, from metabolic and cardiovascular monitoring to neurological and neonatal care. AI integration enhances the predictive and adaptive capabilities of these devices, enabling real-time intervention, personalized health recommendations, and longitudinal tracking of disease progression. The combination of biosensors and AI facilitates precision healthcare, allowing clinicians to tailor treatment plans, improve patient adherence, and optimize outcomes. The convergence of wearable biosensors, continuous monitoring, and AI-driven analytics represents a significant advancement in healthcare delivery. For metabolic health, CGMs and AI models provide real-time glycemic control, risk prediction, and personalized lifestyle guidance. In neonatal care, continuous monitoring of vital parameters combined with predictive AI allows early detection of life-threatening events, improving survival and developmental outcomes. Cardiovascular and neurological applications further illustrate the transformative potential of biosensors in chronic disease management, rehabilitation, and proactive health maintenance. By enabling continuous, non-invasive, and data-driven assessment, biosensors are shaping the future of personalized medicine, offering scalable solutions for real-time health monitoring, early intervention, and improved patient outcomes. In conclusion, biosensors serve as foundational components of modern healthcare ecosystems. Their applications in metabolic, neonatal, cardiovascular, and neurological health highlight their versatility, while integration with AI ensures real-time, predictive, and personalized health management. The ongoing evolution of biosensor technology, in combination with sophisticated computational models, promises to expand their utility further, creating opportunities for preventive care, precision medicine, and enhanced quality of life across diverse patient populations.

**Challenges with AI-Powered Biosensors**

AI-powered biosensors represent a significant advancement in modern healthcare, providing continuous monitoring, early diagnosis, and personalized health management. Despite their promise, these systems face a range of technical, operational, and regulatory challenges that must be addressed to ensure safe, effective, and scalable deployment. Central among these challenges are issues related to data privacy, model personalization, robustness, integration with biological systems, and regulatory compliance. A primary concern in AI-powered biosensors is data privacy. Traditional machine learning methods require centralizing user data in cloud servers for model training, which poses significant security and privacy risks. Health data are particularly sensitive, and unauthorized access could lead to serious consequences for individuals. Federated learning has emerged as a potential solution to this challenge. In this approach, models are trained locally on individual devices, such as smartphones, smartwatches, or wearable biosensors, and only model updates, rather than raw data, are transmitted to central servers. This decentralized methodology allows AI models to learn collaboratively across users while maintaining strict privacy standards, ensuring sensitive health information remains secure. In conjunction with federated learning, Edge-AI techniques are transforming the way data from biosensors are processed. Edge-AI enables the deployment of AI algorithms directly on local devices, reducing reliance on cloud infrastructure. This local processing minimizes latency, enhances privacy, reduces bandwidth usage, and allows for critical real-time decisions in health monitoring, autonomous vehicles, or industrial automation [44,45]. Edge-AI also supports offline operation, allowing devices to function in areas with limited or unreliable internet connectivity. Specialized hardware, such as AI accelerators, combined with optimized neural network architectures, ensures that AI computations are feasible within the resource constraints of wearable biosensors.

Device heterogeneity presents another significant challenge. Variations in sensor types, hardware quality, environmental conditions, and user behavior can result in inconsistent data streams that reduce model performance. Transfer learning offers a solution by leveraging pre-trained models to adapt quickly to new devices or contexts without requiring full retraining. This approach allows AI models to generalize across different populations and hardware while maintaining accuracy. Additionally, biosensors often generate noisy, incomplete, or imbalanced datasets, particularly when detecting rare but critical health events. Such data inconsistencies can significantly impair the predictive accuracy and reliability of AI models, making robust data preprocessing, anomaly detection, and augmentation strategies essential [25,38,39]. Adaptability and interpretability are critical for AI-powered biosensors deployed in dynamic real-world settings. Physiological signals are influenced by numerous factors, including aging, lifestyle changes, illness, or stress. Continual learning is a method that enables models to update incrementally with new data while retaining previously acquired knowledge, preventing catastrophic forgetting. Human-in-the-loop systems further enhance adaptability by incorporating real-time feedback from users or expert annotations, improving model reliability and increasing user trust. For example, users can confirm or correct alerts, while clinicians can annotate complex physiological signals, ensuring that AI predictions remain clinically meaningful. Combining federated learning, continual learning, transfer learning, and human-in-the-loop methodologies allows AI-powered biosensors to achieve higher robustness, personalization, and security in health monitoring applications [27]. Despite algorithmic advancements, the integration of wearable electronics with biological systems remains a fundamental challenge. Biological tissues are flexible, soft, hydrated, and dynamic, whereas most wearable electronics are rigid, brittle, dry, and optimized for controlled conditions. This mismatch introduces mechanical, functional, and operational barriers. Table 4 summarizes these differences, highlighting the need for innovative materials, design strategies, and fabrication techniques to bridge the gap between biological and electronic systems. Flexible electronics, biocompatible polymers, and hybrid bioelectronic interfaces are being investigated to improve comfort, signal fidelity, and long-term wearability, but achieving reliable, long-term integration remains an open challenge.

Operationally, wearable biosensors must cope with dynamic environmental conditions, including motion artifacts, temperature fluctuations, and variations in sweat composition or skin hydration. These factors introduce signal noise and variability that can degrade AI model performance. Advanced signal processing and AI techniques, such as denoising algorithms, adaptive filtering, and context-aware learning, are essential to ensure accurate measurements in real-world settings. Regulatory and reimbursement challenges further complicate the widespread adoption of AI-powered biosensors. Regulatory frameworks for medical devices are evolving to accommodate AI algorithms, but clear, unified standards for evaluating safety, efficacy, and fairness are lacking. Agencies such as the FDA require rigorous clinical evidence, algorithmic explainability, and reproducibility before approving AI-driven medical devices [46]. This regulatory scrutiny is essential to ensure patient safety but can significantly delay the translation of innovations into clinical practice. On the reimbursement side, fragmented policies and the absence of standardized billing codes create financial uncertainty. Insurers often demand longitudinal evidence of clinical benefits and cost-effectiveness, which can be expensive and time-consuming to obtain, limiting the scalability of AI-powered biosensors [47]. Finally, interpretability and user trust remain critical hurdles. Users and clinicians may be hesitant to rely on AI-driven recommendations without clear explanations of how predictions are generated. Explainable AI (XAI) techniques are increasingly integrated with biosensor platforms to provide transparent reasoning, confidence scores, and actionable insights. This not only improves user engagement but also enhances clinical acceptance, facilitating more effective adoption in real-world healthcare scenarios.

In summary, AI-powered biosensors face multidimensional challenges spanning technical, operational, biological, and regulatory domains. Data privacy concerns are addressed through federated learning and Edge-AI, while heterogeneity and noisy data are mitigated with transfer learning and advanced preprocessing. Continual learning and human-in-the-loop systems improve adaptability and interpretability, while material innovations and flexible electronics address mechanical and operational mismatches between biological tissues and electronic devices. Regulatory and reimbursement frameworks remain significant barriers, requiring rigorous evidence and standardized policies. Despite these challenges, integrating advanced AI methods, innovative hardware design, and robust clinical validation positions AI-powered biosensors as a cornerstone of personalized, continuous, and proactive healthcare. Addressing these challenges systematically will be essential to unlock the full potential of biosensors in improving health outcomes, optimizing clinical workflows, and enabling precision medicine on a global scale.

**Future of AI-Powered Biosensors**

The future of AI-powered biosensors is poised for transformative growth, driven by the integration of advanced artificial intelligence techniques, digital twins, and explainable AI frameworks. These technologies will elevate biosensors from passive monitoring devices to intelligent systems capable of providing personalized, predictive, and actionable insights. One key area of innovation lies in diet and hydration management. Optimal hydration is critical for maintaining physical performance, cognitive function, and overall metabolic health. Current wearable technologies can monitor general physiological metrics such as heart rate, sweat rate, or activity level, but they are limited in their ability to track both fluid type and volume with precision [12,31]. Future biosensors, equipped with AI models and connected to sophisticated data ecosystems, will be able to monitor dietary intake, hydration levels, and nutrient consumption in real-time. This capability will enable users to receive personalized guidance for hydration, dietary adjustments, and energy intake, supporting both wellness and disease management strategies. Large Language Models (LLMs) are expected to play a pivotal role in enhancing the intelligence of biosensor systems. LLMs can process vast amounts of multimodal data collected from biosensors, contextualize individual health patterns, and generate tailored recommendations. For example, they can identify correlations between lifestyle factors, physiological responses, and clinical outcomes, guiding interventions such as modifications in exercise routines, dietary intake, or sleep behavior [10,48]. LLMs can also function as interactive agents, enabling users to query their data and receive comprehensible explanations. This bridges a critical gap between the complex outputs of AI models and actionable human understanding, empowering patients and clinicians to make informed decisions based on clear, evidence-supported insights. The integration of natural language processing into biosensor ecosystems ensures accessibility, engagement, and transparency, which are essential for long-term adherence and trust in AI-driven health tools.

Digital twin technology represents another transformative advance in the evolution of AI-powered biosensors. A digital twin is a computational, virtual replica of an individual's physiological and metabolic systems, which continuously integrates real-time data from biosensors alongside historical and contextual health information [49,50]. Unlike static predictive models, digital twins are dynamic and adaptive, capable of simulating interventions and predicting their potential outcomes. For example, a digital twin could simulate the effect of adjusting insulin doses in a patient with diabetes, assess the impact of different exercise regimens on cardiovascular function, or predict the consequences of changes in dietary intake. Continuous real-time data from wearable biosensors feed into these digital twins, ensuring that simulations remain accurate and personalized to the user's current state. This allows for proactive, predictive healthcare where potential complications or suboptimal health behaviors can be identified and corrected before they manifest clinically. Counterfactual explanations further complement these innovations by enhancing interpretability and user trust. Counterfactual methods illustrate how slight changes in behavior or treatment could influence outcomes, providing users with actionable insights. For instance, a counterfactual explanation may demonstrate that increasing daily physical activity by 30 minutes could lower predicted blood glucose spikes, or that reducing sodium intake could positively influence blood pressure trends. By showing the "what if" scenarios, users are empowered to make informed decisions and engage more actively in their health management. Combined with digital twins and AI-driven predictive analytics, counterfactual reasoning ensures that biosensor systems are not only intelligent but also explainable and trustworthy. In addition to these capabilities, future AI-powered biosensors will increasingly leverage federated learning and edge computing to maintain privacy, reduce latency, and ensure real-time responsiveness. Edge-AI will enable continuous local processing of sensor data, while federated learning allows collaborative model updates across devices without compromising user privacy. This combination ensures that predictive and personalized models are both robust and secure, addressing a critical barrier to widespread adoption in healthcare.

Collectively, the convergence of LLMs, digital twins, counterfactual explanations, and edge-AI represents a paradigm shift in healthcare delivery. Biosensors will evolve from passive monitoring devices to proactive partners in health decision-making, capable of predicting disease trajectories, guiding interventions, and offering real-time, personalized recommendations. They will support a truly preventive and precision-based approach to medicine, integrating seamlessly into daily life, and enabling clinicians and individuals to act on health insights before adverse events occur. The trajectory of AI-powered biosensors indicates a future where monitoring, prediction, and intervention converge within a single intelligent system. By providing actionable, explainable, and individualized insights, these devices have the potential to fundamentally transform healthcare, improve patient outcomes, and optimize quality of life. The integration of biosensors with advanced AI technologies ensures a future in which healthcare is continuously adaptive, personalized, and anticipatory rather than reactive, ushering in an era of intelligent, user-centered health management.

**Conclusion:**

AI-enabled wearable biosensors represent a paradigm shift in modern healthcare by enabling continuous, data-driven, and personalized health monitoring across clinical and real-world settings. Their integration with advanced AI techniques allows early detection of disease, prediction of adverse health events, and adaptive interventions tailored to individual physiological profiles. Applications spanning metabolic, cardiovascular, neurological, and neonatal health highlight the versatility and clinical relevance of these technologies. Despite rapid progress, several challenges persist, including data privacy concerns, model robustness under real-world variability, biological–electronic integration, and evolving regulatory frameworks. Emerging solutions such as federated learning, edge AI, explainable AI, and digital twin technologies offer promising pathways to address these limitations. As sensor technologies and AI methodologies continue to mature, interdisciplinary collaboration among engineers, clinicians, and data scientists will be critical. Overall, AI-powered wearable biosensors are poised to become foundational tools in precision medicine, enabling a transition from reactive to proactive and preventive healthcare.

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