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AI-Enhanced Wearable Technology for Human Physiological Signal Detection: Challenges and Future Directions

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In the past decade, advances in IT, microelectronics, materials science, and the growing demand for new medical solutions in an aging society have greatly boosted wearable devices' ability to monitor physiological signals. However, traditional methods of physiological signal analysis have limitations when it comes to processing complex, multimodal data, particularly in the context of nonlinear, non-stationary, and highly personalized information. Recently, AI technologies—especially deep learning, machine learning, and multimodal data fusion—have introduced new solutions for physiological signal analysis, significantly improving the accuracy and real-time performance of signal processing. This work reviews the latest advancements in AI within the realm of wearable physiological signal monitoring. It systematically explores the advantages of AI in enhancing the accuracy of signal extraction and classification, enabling personalized health monitoring and disease prediction, and optimizing human–computer interaction. Additionally, it analyzes specific applications of AI in the analysis of bioelectric, mechanical, chemical, and temperature signals. The work also discusses challenges such as data privacy, algorithm generalization, real-time processing, and model interpretability. Finally, it prospects the development trends of AI-driven wearable physiological monitoring technology, focusing on materials, algorithms, chips, and multidisciplinary collaborative innovation.

1. Introduction

With the global population aging and public health demands intensifying, continuous, accurate, and personalized physiological monitoring has become a critical issue in modern medicine and health management.[1] Traditional physiological signal acquisition methods, such as 12-lead electrocardiography (ECG) or full polysomnography (PSG), are primarily designed for short-duration, high-resolution data collection in controlled clinical settings. While effective for episodic diagnostics, these systems typically require bulky infrastructure and specialized personnel, which constrains their deployment in real-world or home-based scenarios.[2,3] Moreover, their limited temporal coverage fails to capture dynamic physiological changes that unfold over extended periods—particularly relevant for chronic condition management and early-stage detection. In contrast, the rapid development of wearable multimodal sensing systems and AI-enabled data interpretation tools has enabled real-time, longitudinal monitoring across diverse physiological domains, offering enhanced ecological validity, user compliance, and opportunities for proactive health interventions.[4,5] These limitations underscore an urgent need for portable, non-invasive, and intelligent solutions that enable ubiquitous health monitoring in everyday settings.[6–9]

In response to this demand, recent advances in information technology, microelectronics, flexible materials, and communication networks have driven the rapid development of wearable physiological sensors.[10–12] These next-generation devices offer features such as low power consumption, real-time sensing, and seamless body integration, enabling dynamic and multimodal monitoring of physiological states—including bioelectrical signals such as ECG, electroencephalography (EEG), and electromyography

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(EMG); mechanical signals like motion and pressure; chemical indicators found in sweat and tears; and thermal signals.[13–15] As such, wearable sensors have emerged as a foundational technology in applications ranging from daily health tracking and disease prevention to clinical diagnosis and rehabilitation.[16–19]

Parallel to sensor innovation, the integration of AI—particularly deep learning, machine learning, and multimodal data fusion techniques—has significantly expanded the analytical capability of physiological monitoring systems.[20,21] AI algorithms empower wearable devices to autonomously filter noise, extract meaningful features, and interpret complex biosignals with improved precision. For instance, noise artifacts in ECG/EEG/EMG signals can be effectively suppressed;[22–33] gait recognition and fall prediction from mechanical signals can be enhanced;[34–36] biochemical markers in sweat and tears can be calibrated in real-time;[37,38] and thermal data can be fused with other physiological indicators to assess disease progression more intelligently.[39,40] These developments collectively transform wearable systems from passive data-acquisition platforms into active decision-support tools, thereby providing substantial benefits for early disease detection, risk prediction, and personalized intervention.[41–46]

Despite these advancements, significant challenges hinder the large-scale deployment and clinical translation of AI-driven wearable monitoring systems. On the algorithmic level, issues such as poor model generalizability across populations, limited interpretability, and high data annotation costs remain unresolved.[47–49] Recent studies have explored solutions including transfer learning, federated learning, and large language models to improve generalizability across heterogeneous populations and sensor modalities.[50,51] To address the black-box nature of AI, explainable AI (XAI) frameworks—such as SHAP, LIME, and saliency maps—have been increasingly integrated into biomedical pipelines to enhance model transparency and facilitate clinical trust.[52,53] Additionally, emerging strategies like automatic data annotation, weak supervision, and active learning have demonstrated potential in reducing reliance on expensive expert-labeled datasets.[54,55] From a hardware perspective, battery life, user comfort, and the long-term stability of sensors pose design constraints.[56] Hybrid sensor systems and ultra-low-power architectures have been investigated to extend operational longevity and improve wearability in real-world environments.[57] Furthermore, systemic obstacles—including lack of standardization, data interoperability, and privacy concerns—continue to restrict broader integration into healthcare infrastructure.[58] Standard-driven interoperability frameworks and privacy-preserving machine learning techniques such as differential privacy and federated analytics are being developed to mitigate these barriers.[59,60]

In light of these challenges, this review systematically summarizes the recent progress in AI-supported wearable physiological signal monitoring (**Figure 1**). We first analyze the technical mechanisms and performance boundaries of AI in processing bioelectrical, mechanical, chemical, and thermal signals. Next, we dissect critical bottlenecks across the data-algorithm-hardware-system chain, such as energy constraints, security risks, and clinical compliance. Finally, we propose future development directions—including edge computing, self-powered materials, and federated learning—as potential solutions to build efficient, secure, and sustainable wearable health monitoring systems. This work aims to provide theoretical insights and practical references for researchers and industry stakeholders committed to advancing intelligent health technologies.

2. Classification and Application of AI-Enabled Physiological Signals Wearable Sensors

2.1. AI-Enhanced Bioelectrophysiological Signal Monitoring

Bioelectrical signals are electrical potential changes generated by body organs, reflecting the activity of the heart, brain, and muscles. Common bioelectrical signals include the ECG, EEG, EMG, electrooculographyl (EOG), electrodermal activity (EDA), and electrogastrogram (EGG). Skin electrodes are typically used to record these electrophysiological signals.[22,61–66] In recent years, advancements in flexible electronics and dry electrode materials have enhanced the comfort and signal quality of electrophysiological signal sensors, enabling long-term, stable physiological monitoring.[67–70] This section reviews three widely used devices: the ECG, EEG, and EMG.

Wearable ECG devices measure the electrical activity of the heart in real time, facilitating abnormal heart rate analysis and arrhythmia detection.[71–73] A significant challenge with ECG technology is minimizing discomfort and irritation caused by the electrodes.[74] Flexible, wearable ECG signal sensors allow for remote, real-time monitoring of heart conditions with minimal disruption to the user's daily activities. For instance, Chung et al. developed a flexible, skin-like wireless monitoring system for neonatal care (**Figure 2A**) that tracks vital signs in real time without interfering with parent-child contact. The inherently thin, soft mechanical properties of the sensors allow for adhesion via van der Waals forces alone. The mechanical decoupling provided by the microfluidic channel can significantly reduce skin interface stress associated with the natural motion of the neonate. Compared to designs without microfluidic channels, the forces at steady-state peeling rates are different by approximately a factor of 10.[75] By adopting biomimetic skin patches and wireless transmission technology, novel devices not only overcome the mechanical discomfort of traditional electrodes but also achieve a balance between medical-grade signal quality and wearing comfort. These advancements establish the technological foundation for continuous extra-hospital cardiovascular monitoring, paving the way for constructing more intelligent personal health management systems.

Wearable EEG devices are commonly used for monitoring sleep stages and predicting seizures.[76,77] Traditional EEG monitoring devices struggle to achieve portability while maintaining accuracy.[78] The advancement of wearable technology has begun to address this issue. Currently, EEG signals collected by wearable devices have reached a level of accuracy that allows for reliable classification. For example, Qiao et al. proposed a high-comfort electronic skin (Figure 2B) made from laser-etched graphene (LSG) and polyurethane (PU) nanonetworks, which accurately detects electrophysiological signals such as ECG, EEG, and EOG. In this study, EEG signals were classified using a combination of time-domain and frequency-domain convolutional neural networks (CNN), effectively detecting attention states.[79] Current wearable EEG systems have broken the spatial constraints of traditional EEG caps through material innovation and optimization,

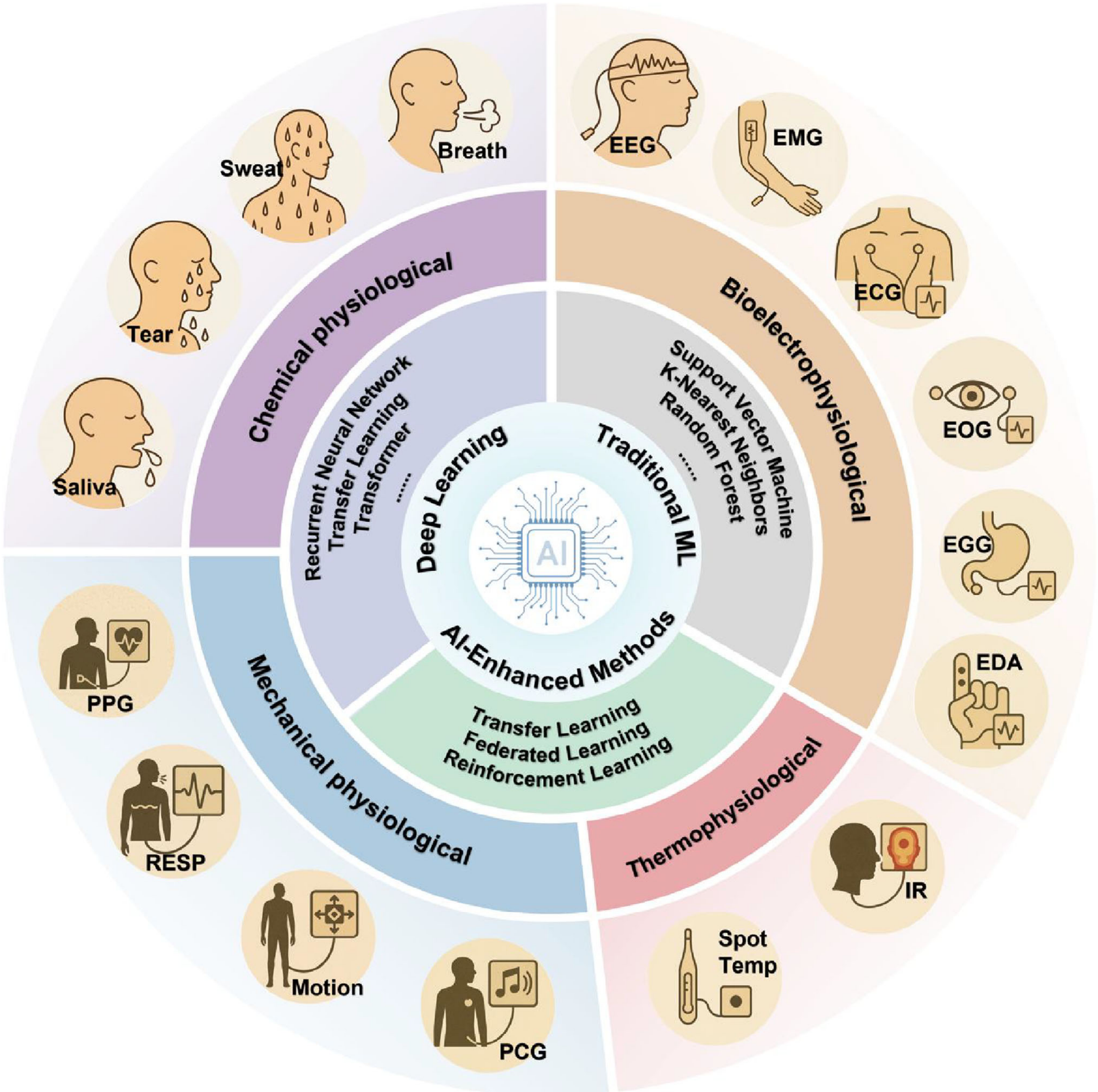

Figure 1. Overview of AI-enhanced biosignal sensing methods in physiological modalities.

enabling 24/7 cognitive state tracking while maintaining clinical accuracy.

EMG sensors record muscle activity in various body parts, playing a crucial role in analyzing the daily activity levels of individuals and providing rehabilitation feedback for those with disabilities. Wearable EMG sensors have a broad range of applications, enabling the monitoring and analysis of complex body movements. For example, Chen et al. developed a wearable echomyography (EcMG) system based on a single ultrasound transducer, which is encapsulated within a soft elastomer and integrated with a flexible circuit and onboard battery to enable wireless and continuous monitoring of deep muscle activity with sub-millimeter resolution. The system was applied to detect diaphragm motion for respiratory pattern analysis and to recognize hand gestures from forearm muscle activity using a customized deep learning algorithm, achieving a mean joint angle estimation error of only 7.9°, thereby demonstrating its potential for clinical respiratory monitoring and human–machine interaction.[80] Lo et al. proposed a stretchable porous polydimethylsiloxane (PDMS) sponge electrode (Figure 2C) that utilizes a PEDOT:PSS conductive polymer coating to significantly reduce electrode-skin contact impedance and improve the signal-to-noise ratio (SNR)

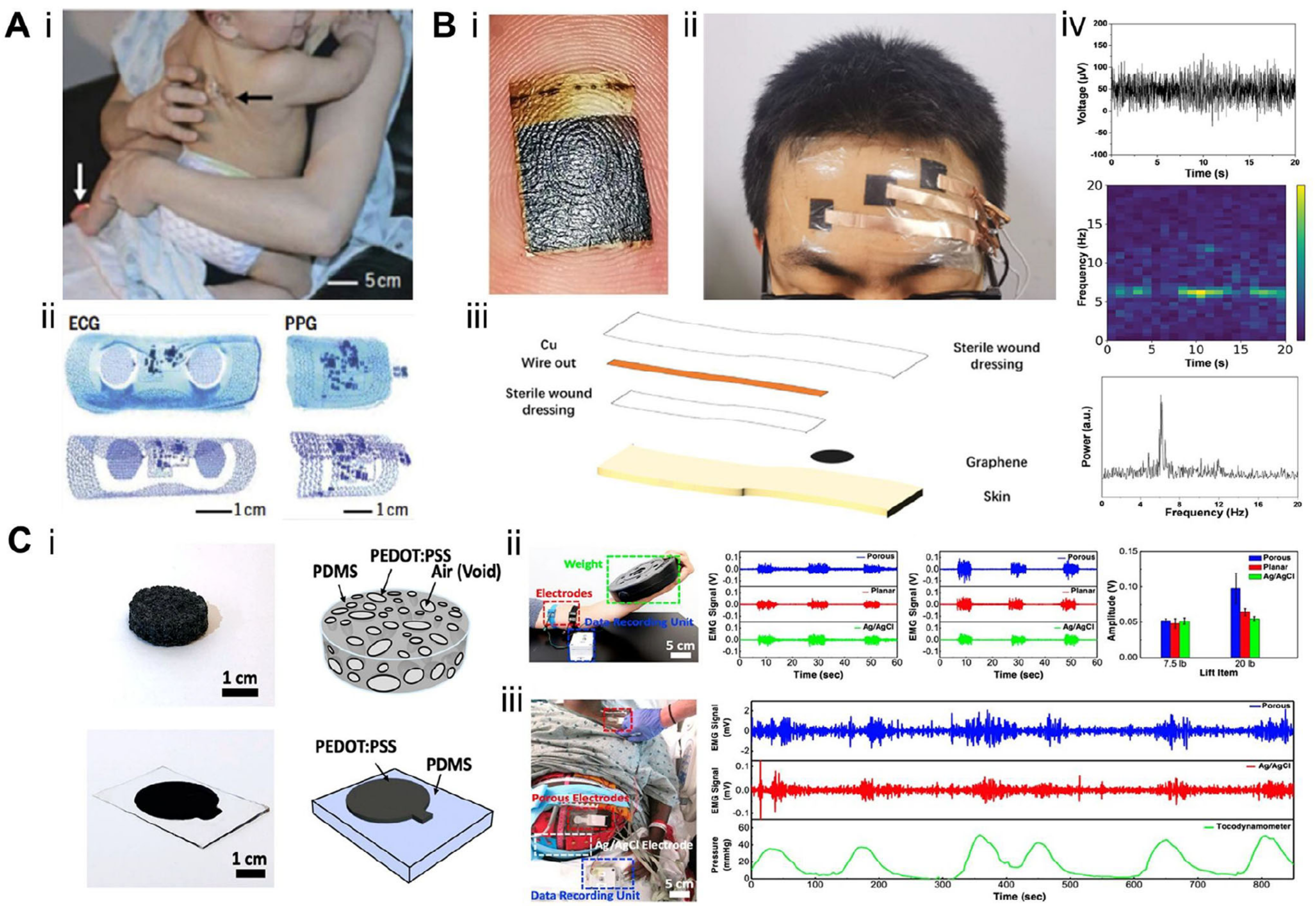

Figure 2. Wearable sensor for bioelectrophysiological signal acquisition. A) i. A mother holds her baby while wearing a photoplethysmography (PPG) device on her feet and an ECG device on her back. ii. Images and finite element modeling results of the ECG and PPG devices bent around a glass cylinder. Reproduced with permission.[82] Copyright 2019, Published by Elsevier Inc. on behalf of The American Association for Thoracic Surgery. B) i. The laser scribed graphene (LSG)/ polyurethane (PU) nanonet on the finger displays a clear fingerprint shape (the yellow part represents the graphene oxide (GO)/PU nanonet, while the black part represents the LSG/PU nanonet). ii. EEG electronic skin is attached to the tester's forehead. iii. Schematic diagram of the EEG e-skin. iv. The EEG signal of the tester when watching 6 Hz shining, the frequency spectrum of the 20 s signal, and the FFT spectrum of the 20 s signal. Reproduced with permission.[79] Copyright 2021, Wiley-VCH GmbH. C) i. Photographs and a schematic diagram of a sponge electrode and a PEDOT:PSS film printed directly on a flat PDMS substrate. ii. The setup for measuring the EMG signal from the contraction of biceps, EMG signals measured using various kinds of electrodes when the subject was lifting a 7.5 and 20-lb weight, and a comparison of the EMG signal amplitude measured with sponge, planar, and commercial Ag/AgCl electrodes. iii. The setup for recording EMG signals from uterine contraction activities in a clinical setting and a comparison of EMG waveforms recorded from our porous electrodes and in-house built data recorder, the commercial BioSemi active Ag/AgCl electrodes, and the BioSemi biopotential measurement system and the corresponding uterine contractions recorded from a tocodynamometer. Reproduced with permission.[81] Copyright 2022, American Chemical Society.

for long-term, high-quality bioelectrical signal monitoring. The research team applied sponge electrodes to monitor uterine contractions, demonstrating superior performance compared to conventional Ag/AgCl electrodes.[81] This technology not only provides quantitative assessment tools for rehabilitation medicine but also creates new pathways for human-machine interaction and intelligent prosthetic control through integration with Internet of Things (IoT) platforms. Future efforts must address multichannel signal crosstalk to enhance complex motion decoding capabilities.

The research on new wearable bioelectric sensors has indeed advanced sensing technology toward a more comfortable and portable direction; however, several issues persist in practical applications. On one hand, the amplitude of electrophysiological signals is weak, making them susceptible to external electromagnetic interference and environmental noise, which can lead to a decline in signal quality and an increase in measurement errors. On the other hand, the contact state between the sensor and the skin significantly affects signal stability. Factors such as changes in electrode position, poor contact, or variations in skin humidity can cause signal distortion or loss. Additionally, the inherent nonlinear and non-stationary characteristics of electrophysiological signals, along with the interference from motion artifacts, complicate signal processing. Challenges such as the long-term stability of sensor materials and designs, wearing comfort, and the accurate extraction and analysis of complex signals remain critical in the research process.

Simultaneously, as sensing technology evolves, the number of signal channels that can be collected by sensing equipment is increasing. The processing of bioelectrical signals faces complex challenges, including a large number of channels, vast amounts of data, and noise interference. The introduction of AI algorithms can facilitate efficient noise removal, artifact elimination, and feature recognition, enabling researchers to extract meaningful health information from the signals more effectively.[22–33]

Machine learning can automatically detect abnormal cardiac events from ECG readings, enhancing the accuracy of early heart disease diagnosis.[77,82–90] For example, Rahman et al. developed a deep learning-based remote ECG monitoring and syncope detection system for identifying atrial fibrillation (AF) and syncope due to AF. The ECG signals are processed using Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) models. LSTM mitigates the vanishing gradient problem inherent in traditional RNNs and is particularly well-suited for processing ECG signals, which are characterized by strong temporal continuity and significant variability. Training the LSTM model on the MIT-BIH arrhythmia database resulted in a classification accuracy of 97.61%. The proposed system outperformed commercially available systems such as the Kardia Mobile ECG.[87] Huang et al. introduced a novel input method based on time characteristics for the classification of ECG signals, achieving improved accuracy. By incorporating the RR interval (the time between two R waves) of the ECG signal as the time scale, a time transformation of the original heartbeat signal is generated. This Time Representation Input is created by combining a CNN-LSTM structure with an attention mechanism. LSTM networks effectively compensate for the limited temporal feature extraction capabilities of CNNs, enabling more accurate modeling of time-dependent patterns in sequential data. A lightweight, high-precision model (**Figure 3**A) was developed to classify five types of heartbeats (including normal and four abnormal types) from the MIT-BIH arrhythmia database, achieving an average accuracy of 98.95%, sensitivity of 96.54%, and specificity of 99.38%.[83] Currently, the detection and classification of abnormal ECG signals, such as arrhythmia, have reached a relatively high level of accuracy.

Machine learning algorithms applied to EEG signal analysis can identify subtle features like epileptic discharges or emotional states.[76,91–94] Tveit et al. proposed and validated the Standardized Computer-based Organized Reporting of EEG-AI (SCORE-AI) model for the automatic interpretation of routine clinical electroencephalograms (EEGs). By training on over 30000 EEG recordings, SCORE-AI can differentiate between normal and abnormal EEGs and categorize the latter into focal epileptoid, generalized epileptoid, focal non-epileptic, and generalized non-epileptic types. Its diagnostic accuracy is comparable to that of human experts, demonstrating high sensitivity (86.7%) and specificity (90%) across multiple independent test sets. In benchmark comparisons, SCORE-AI outperformed other published AI-based EEG models, including Encevis, SpikeNet, and Persyst. Notably, while models like Persyst and Encevis achieved higher sensitivity, they exhibited markedly lower specificity (as low as 3%), leading to an increased rate of false positives. In contrast, SCORE-AI achieved a balanced performance with both high sensitivity and high specificity, resulting in the highest overall classification accuracy (88.3%) among all tested models. This balanced performance highlights the model's clinical reliability, particularly in distinguishing between epileptiform and non-epileptiform patterns with minimal false alarms, and positions SCORE-AI as a viable tool for supporting diagnostic decision-making in clinical neurophysiology.[95] EEG signals are prone to interference, making their identification and classification more challenging compared to other forms of electrophysiological signals, thus placing higher demands on EEG classification algorithms. In response to this challenge, many researchers have proposed innovative solutions. For instance, Shin et al. developed a brain-AI Closed-loop system (BACLoS) that enables continuous recording of high-quality EEG signals, particularly error-related potentials (ErrPs), using a wireless EEG measurement device resembling earplugs, along with tattoo-like electrodes and connectors. This system captures the cognitive responses of humans to unexpected machine actions, while AI classifies the received EEG data through deep learning to adjust or reinforce decisions based on the presence or absence of ErrP signals (Figure 3B).[96] Such systems can optimize AI decisions based on human feedback, offering more rational solutions to complex situations.

The introduction of AI in EMG analysis, which can more accurately identify and classify high-resolution signals, enables devices to establish more signal acquisition channels. This advancement can lead to more precise rehabilitation training and improved recognition of patient motor intent. recognition.[97] For example, the NeuroLife EMG Sleeve, developed by Tacca et al., captures high-resolution muscle activity signals by positioning up to 150 electrodes on the forearm. In combination with machine learning algorithms, it achieves highly accurate classification of 37 hand movements, with an accuracy of up to 97.3%, and continuously predicts 23 finger joint angles (R^2 up to 0.884).[98] Currently, the collection of physiological signals has become portable through wearable devices, making the accurate training and classification of the collected data in real-time a significant challenge. Moin et al. developed a wearable high-density surface myoelectric (sEMG) sensing system that enables local adaptive learning and real-time reasoning for gesture recognition. The hyperdimensional computing (HDC) algorithm was selected due to its simplicity, fast learning capabilities, and inherent robustness to noise—making it well-suited for low-power, in-sensor gesture recognition applications. Unlike conventional machine learning models such as SVMs or LDA that require iterative retraining, HDC enables lightweight on-device training and model adaptation without sacrificing classification performance. This system utilizes the HD computing paradigm to convert physiological signals, such as sEMG, into high-dimensional vectors (hypervectors), allowing for the execution of complex tasks through simple computational operations. The system recognized 13 gestures with 97.12% accuracy after a single training session for each gesture and maintained 92.87% accuracy when extended to 21 gestures (Figure 3C).[99] The localization of the classification recognition process facilitates rapid adaptation and processing of complex physiological signals, and this technique can also be applied to other types of physiological signal monitoring.

In summary, AI can significantly enhance the recognition accuracy and processing efficiency of complex bioelectrical signals, demonstrating strong generalization across various signal types. Application scenarios include arrhythmia and cardiac arrest detection, mood and stress monitoring, Parkinson's disease diagnosis assistance, and personalized health management. Additionally, the integration of AI with wearable devices enables real-time monitoring and remote health management. However, current challenges include the high cost of data annotation, poor

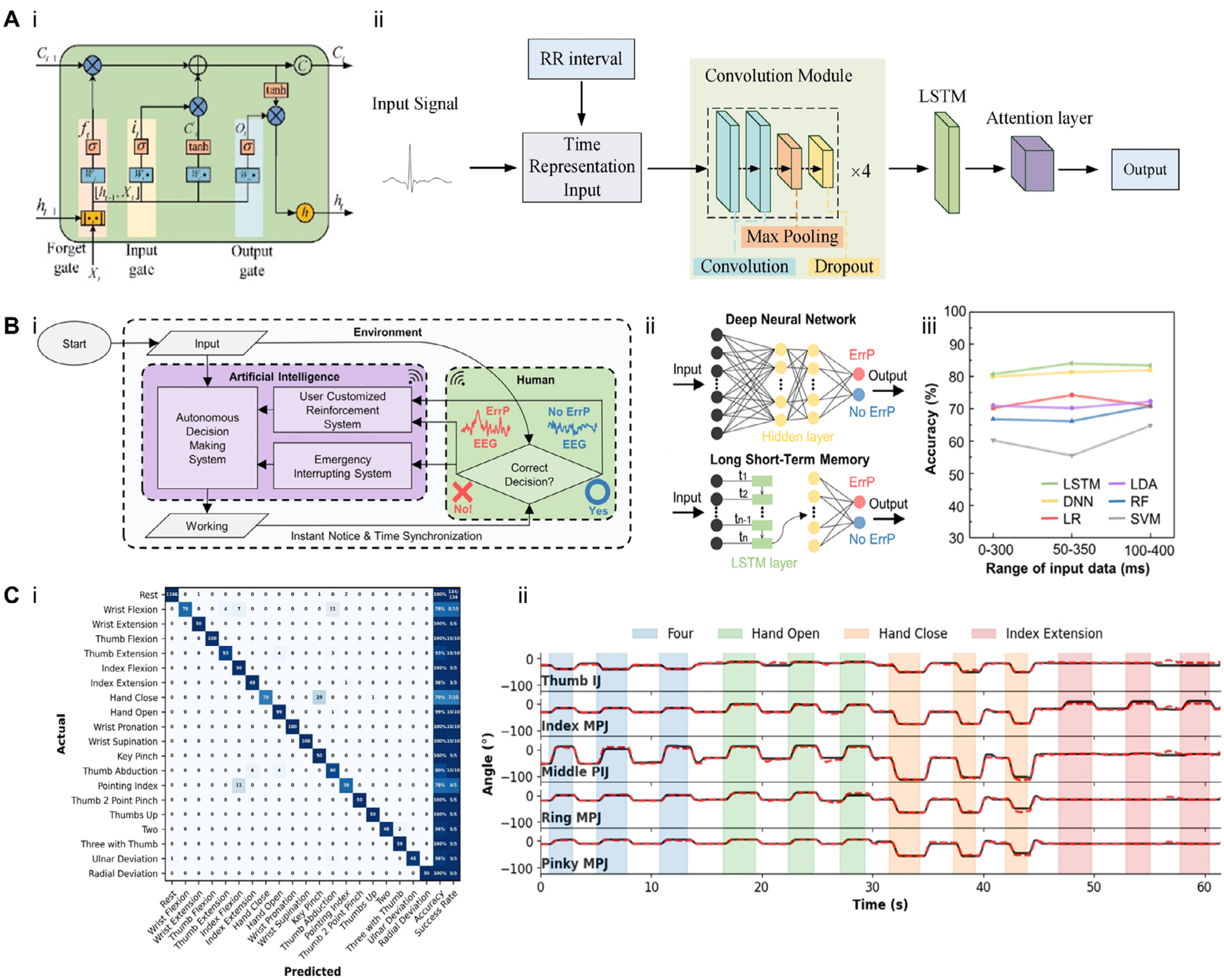

Figure 3. Wearable monitoring of bioelectrophysiological signals is based on an AI algorithm. A) i. Structure of LSTM memory block. ii. A 10-layer CNN-LSTM network processes time representation inputs, consisting of 8 convolutional layers, 1 LSTM layer, and 1 attention layer. Reproduced with permission.[83] Copyright 2023, Elsevier Ltd. B) i. Brain–AI Closed-Loop System (BACLoS) flow charts are implemented in a closed-loop feedback algorithm for ErrP signals based on electroencephalogram data, reinforcing and correcting the autonomous decision-making of machines. ii. Deep neural network (DNN) architectures and long short-term memory (LSTM) architectures consist of multi-layer recurrent neural networks. iii. Single-trial classification accuracies by time range of the input EEG data for training and validation using deep learning and traditional machine learning algorithms: logistic regression (LR), linear discriminant analysis (LDA), random forest (RF), and support vector machine (SVM). Reproduced with permission.[96] Copyright 2022, The Authors. C) i. Exemplary confusion matrix from mid-window decoding of the mixed dataset for subject 1. Total bin-wise accuracy and success rate by movement are shown in the last two columns. ii. Exemplary simulated real-time joint angle predictions (red-dashed) compared to the ground truth (black) joint angles in a 1 min snippet of data from the sequential dataset of subject 1. Reproduced with permission.[98] Copyright 2024, The Author(s).

compatibility among different data sets, model interpretability, and the need for real-time algorithms. Future research should focus on developing more efficient and robust algorithms and optimizing the integration of sensors and AI systems to enhance their application capabilities and user experience in real-world scenarios.

2.2. AI-Enhanced Mechanical Physiological Signal Monitoring

Mechanical physiological signals encompass various parameters related to movement, mechanics, and deformation of the human body, including body movement, pulse pressure, and breathing. These signals are typically obtained through wearable devices such as accelerometers, gyroscopes, pressure sensors, and strain gauges.[100–102] They contain rich physiological information about the human body and hold significant analytical value.

For instance, the inertial measurement unit (IMU), which typically includes a three-axis accelerometer and gyroscope, is widely employed in wearable motion monitors to record gait, posture, exercise intensity, and other metrics that assist in assessing daily activity and fall risk.[34,61,103–106] Pan et al. developed a human fall detection method using multi-sensor data fusion and the SVM algorithm. By simulating falls and daily activities of 100 volunteers, they analyzed the four stages of falls and extracted three characteristic parameters to describe changes in human acceleration and posture. The method achieved a sensitivity of 96.67% and a specificity of 97%, demonstrating the feasibility of creating a fall detection system based on wearable intelligent devices.[35]

Physical sensors are essentially electromechanical devices that convert mechanical stress or motion into electrical signals, capable of sensing everything from subtle touch pressure and pulse pulsation to larger joint movements.[107–110] These mechanical sensors are typically categorized into pressure sensors and strain sensors. Pressure sensors detect changes in force or pressure applied to them, such as arterial pulsation pressure;[64] strain sensors measure variations in resistance or capacitance due to material deformation and are used to capture the amplitude of human motion.[80,111] Li et al. developed a glove equipped with multimodal sensors to quantify the severity of hand dysfunction in patients with Parkinson's disease and assess hand versatility. The glove employs built-in flexible film pressure sensors and flexible bending sensors to gather hand kinematic data, including finger bending angles, hand muscle strength, and tremor signals, and utilizes various algorithms to process and analyze these signals (**Figure** 4A). Experimental results indicated that the assessments of hand flexibility, muscle strength, and stability made with the gloves were highly consistent with clinical observations (Kappa values of 0.833, 0.867, and 0.937, respectively). This glove provides objective data to support the rehabilitation of Parkinson's patients, aiding doctors in crafting targeted rehabilitation programs and enhancing the efficiency of hand function recovery.[112]

Pressure sensors can be integrated into insoles or seat cushions to measure pressure distribution in gait analysis or to monitor sitting pressure, aiding in the prevention of bedsores for patients on long-term bed rest.[113,114] Zhang et al. proposed a wearable sensor system based on triboelectric nanogenerators (TENG) for gait analysis and waist motion capture. This system achieved 98.4% accuracy in recognizing different walking patterns using a smart insole equipped with two TENG sensors (Figure 4B). Additionally, it can monitor Parkinson's disease symptoms and detect falls. By incorporating wearable devices into lower limb rehabilitation robots (iReGo), the potential of sensor systems for user identification, motion monitoring, robot-assisted training, and game-assisted training was demonstrated.[115]

Flexible strain sensors can be attached to the chest and abdomen, expanding and contracting with respiratory movements to monitor respiratory rate and depth.[82,116] Qi and Aliverti introduced a novel wearable Breathing and Activity Monitoring (WRAM) system for continuous, real-time tracking of breathing patterns during daily activities. This system utilizes a chest strap sensor that simultaneously captures breathing signals and acceleration data, identifying 15 complex human activities through a hierarchical classification (HHC) algorithm. The system achieved an average accuracy rate of 97.22%, with a prediction time of 0.0094 s, and it can monitor multiple users in real time, offering a new approach to precision medicine and health status monitoring.[116]

Despite the strong performance of these wearables in experiments, challenges remain in practical applications. Accurately distinguishing the actions of interest within complex human activities is particularly difficult, as actual human behavior often involves a combination of multiple actions, and performance can vary among different groups. Furthermore, in real-world environments, the stability and accuracy of sensor signals may be compromised, complicating algorithmic analysis. Therefore, developing intelligent algorithms that can adapt to individual and environmental variations is a crucial area of research. Additionally, improving the integration of information from wearable devices with clinical diagnoses and creating a standardized evaluation system are important directions for future research.

To measure reliably in wearable situations, sensor materials must be highly soft and stretchable to accommodate the deformations of skin or fabric. As a new type of biomedical electronic equipment, flexible sensors show great potential in the field of physiological signal monitoring due to their unique flexibility, lightweight, and wearability. Compared with traditional rigid sensors, the design concept of flexible sensors fully considers the complex physiological environment and human movement, which can better fit the human skin, realize continuous and real-time monitoring of physiological signals, and provide users with higher comfort and convenience. In recent years, with the rapid development of materials science, nanotechnology, and electronic engineering, flexible sensors have been widely used in physiological signal monitoring.[36,63,72,111,118–135] Ma et al. developed a fabric-integrated pressure sensor utilizing skin core fibers, which offer high sensitivity, fast response, and excellent stability. When woven into fabric sensors, these fibers can accurately capture physiological signals generated by human movement and sitting positions in real time, providing long-term comfort when integrated into various clothing parts. The system, which combines wet-spun skin core aerogel fiber, a signal conversion module, and a deep learning model, can identify sitting posture with 98% accuracy (Figure 4C), offering a reliable solution for monitoring sub-health status and correcting unhealthy lifestyles, while also presenting a novel approach for the mass production of the next generation of smart textiles.[117] Hui et al. developed a gradiently foaming ultra-soft hydrogel sensor for highly deformable, crack-resistant, and sensitive conformal human-machine interfaces. With an ultra-low Young's modulus (1.68 kPa), high sustainable strain (1411%), enhanced fracture toughness (915.6 J m^{-2}), and high sensitivity (tensile sensitivity 21.77, compression sensitivity 65.23 kPa^{-1}), it can accurately obtain and recognize the operator's gesture commands for remote control of surgical robots and other equipment. This kind of sensor not only has excellent mechanical performance but also can realize high sensitivity monitoring of physiological signals, which provides a new solution for the field of medical health and human–computer interaction.[136] These research advances show the potential of flexible sensors in physiological signal monitoring. However, to achieve large-scale application, it is necessary to further solve the problems of durability, cost control, data processing, and transmission of flexible sensors.[137,138] In addition, how to better integrate these new sensors with existing medical equipment and information systems is also the direction of future research.

On the other hand, traditional signal analysis methods struggle to meet the demands for high precision and efficiency due to the large amplitude and frequency variation range of human

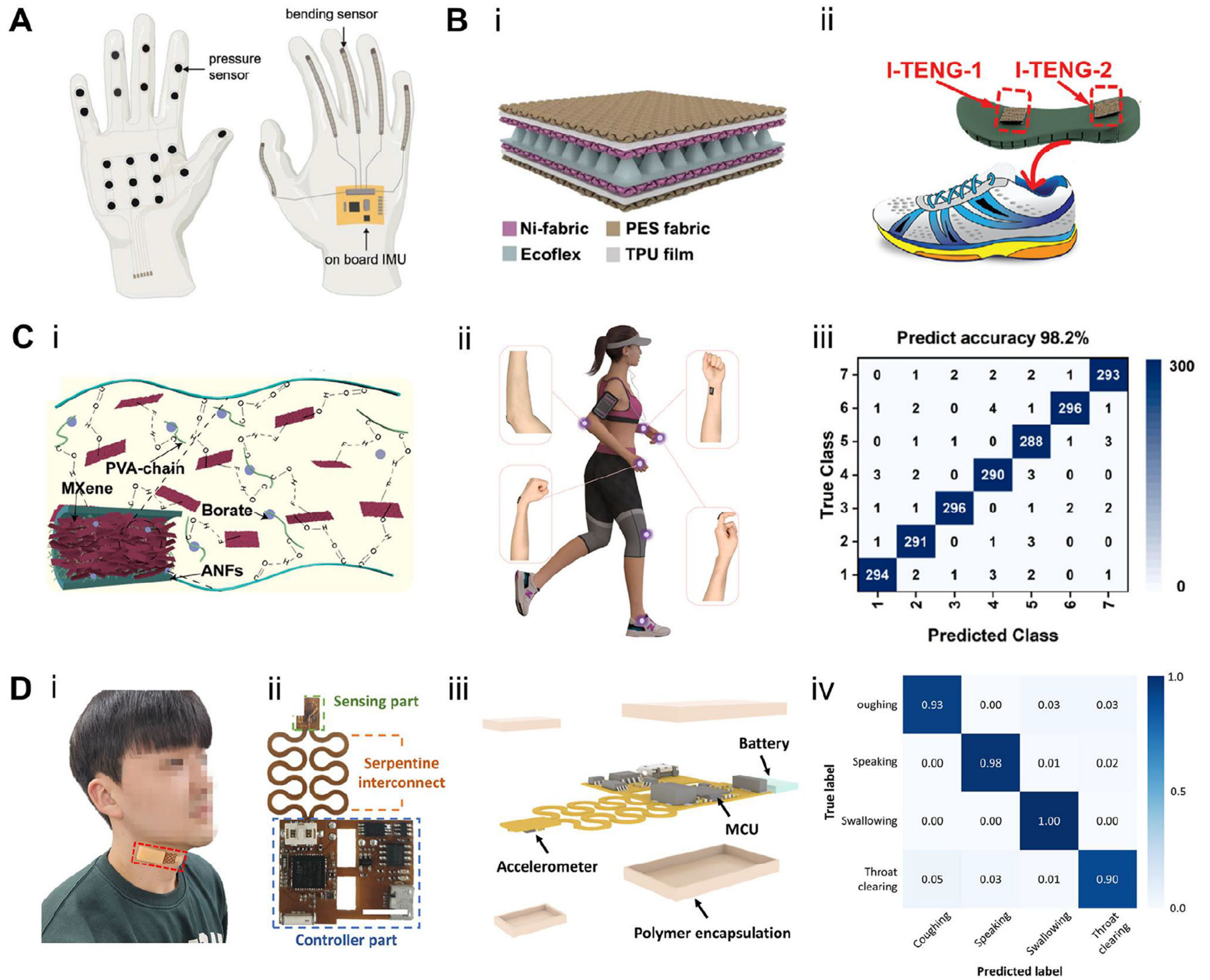

Figure 4. Wearable sensors for acquiring mechanical physiological signals. A) A depiction of the inner layering of the multimodal sensor glove and the layout of each sensor. Flexible film pressure sensors are located on the palmar side of the glove, with detection points corresponding to the palm, purlicue, middle phalanges, and distal phalanges. Flexible bending sensors are positioned on each dorsal phalanx. The IMU and Microcontroller Unit (MCU) are integrated on the back of the glove. Reproduced with permission.[112] Copyright 2023, Wiley-VCH GmbH. B) i. Structure and working principle of TENG sensors based on textile materials. ii. Structure of the TENG-based smart insole, featuring two TENG sensors labeled I-TENG-1 and I-TENG-2. Reproduced with permission.[115] Copyright 2021, Wiley-VCH GmbH. C) i. The longitudinal section of the MPA fiber and the enlarged mechanism diagram. ii. MPA-7 fabric sensors detect various physiological signals, including different degrees of elbow flexion, pulse, wrist flexion, finger bending at different angles, ankle flexion, finger tapping, and knee flexion. iii. Confusion matrix for seven postural types. Reproduced with permission.[117] Copyright 2024, Elsevier Ltd. D) i. One subject wears a soft, skin-attached laryngeal vibration sensor (STVS) positioned prominently in the larynx. ii. No enlarged image of the polymer-encapsulated STVS is provided; the sensing part of the STVS forms conformal contact with the neck skin. iii. Image of the STVS with integrated components. iv. Normalized confusion matrix of the ensemble-based deep learning model on test datasets, with classification accuracy for all events exceeding 90%. Reproduced with permission.[36] Copyright 2025, Springer Nature Ltd.

motion signals, along with noise interference. With advancements in AI, AI algorithms are playing an increasingly prominent role in mechanical signal processing.[139–143] Through technologies such as deep learning, AI algorithms can automatically extract features from signals to achieve accurate classification and analysis of complex mechanical physiological signals.

For example, in human activity monitoring, distinguishing motion signals with varying amplitudes presents a challenge. Machine learning can assist in accurately classifying motion patterns that exhibit similar amplitudes or morphologies.[34,80,108,113,114,118–120,142–153] Song et al. proposed a multimodal depth-integrated classification system utilizing wearable vibration sensors to detect throat-related events. The soft skin-attached throat vibration sensor (STVS) developed can accurately record throat vibrations. They designed a deep learning model to classify events by integrating several deep neural networks: WaveNet, ResNet50, and EfficientNet. This model leverages the multimodal acoustic characteristics of throat-related events, utilizing WaveNet for time series data and ResNet50 and EfficientNet for spectral image data. WaveNet's dilated convolution structure effectively captures dependencies in time series data, which is crucial for identifying short-term events like swallowing and coughing. Meanwhile, ResNet50 and EfficientNet excel in image classification, enabling them to analyze spatial features in spectral images and differentiate various throat activities. The prediction results from these networks are combined using the LightGBM integration algorithm, resulting in a final classification model that achieves an impressive accuracy of 95.96% on the test dataset, significantly surpassing previous studies (Figure 4D).[36] Zhou et al. developed a machine-learning-assisted wearable gesture-speech translation system capable of accurately translating American Sign Language (ASL) into speech. This system comprises a scalable sensor array (YSSA) made from wearable yarn and a wireless printed circuit board (PCB) that offers high sensitivity and a rapid response time. The system analyzes 660 body language gestures using a machine learning algorithm. Principal component analysis (PCA) simplifies high-dimensional signals into key features, enabling effective feature extraction and dimensionality reduction. This process produces more distinct feature vectors for subsequent classification. SVM utilizes these features to accurately classify gesture signals by identifying the optimal hyperplane. Its kernel function accommodates nonlinear relationships, further enhancing classification accuracy. These algorithms demonstrate adaptive learning and generalization capabilities, achieving a recognition rate of 98.63% and a recognition time of under 1 second. Additionally, it can translate gestures into speech in real time across different individuals and environments, offering a novel solution for bridging body language and speech communication.[124] Wen et al. developed an intelligent glove system based on AI for sign language recognition and two-way communication in virtual reality environments. The system captures hand motion signals through gloves equipped with TENG sensors and analyzes these signals using an optimized CNN deep learning model. CNN can effectively capture key features and complex patterns in time series signals using convolutional and pooling layers. It is capable of recognizing both individual gestures and complete sign language sentences. The recognition accuracy achieved is 91.3% for 50 words and 95% for 20 sentences (**Figure** 5A). This ability to recognize sentences greatly enhances the system's practicality and interactivity, broadens its application scope, and is expected to improve two-way communication between hearing-impaired individuals and those without hearing impairments.[128] Yang et al. developed a triboelectric sensor and pressure feedback ring (TSPF-Ring) for rehabilitation training of upper limb sensory impairment after a stroke. The system detects multidimensional tactile changes, such as pressure, proximity, and texture, with high sensitivity through triboelectric sensors and converts these changes into visual stimulation. Tactile signals encompass a variety of local features, including changes in waveform, amplitude, and frequency. CNNs can progressively extract higher-level features through multiple layers of convolution and pooling. By learning from a substantial amount of training data, CNNs can accurately classify signals associated with different textures, materials, and shapes, achieving an accuracy rate exceeding 99%. Additionally, the pneumatic actuator provides adjustable tactile feedback ranging from 0 to 12 N (Figure 5B). Electrophysiological experiments demonstrate that the system can promote the activation of the sensorimotor cortex in stroke patients, which is expected to enhance hand sensory function and offer a new wearable solution for sensory rehabilitation.[154] These applications demonstrate the significant potential of AI in complex pattern recognition and signal processing, offering a pathway for the broader implementation of wearable technology across various fields.

The application of AI algorithms not only significantly improves the accuracy of mechanical physiological signal processing but also paves the way for personalized medicine and health management. Studies have shown that analyzing accelerometer data in conjunction with AI can identify abnormal gait and motor degradation early, facilitating the early diagnosis and fall warnings for diseases such as Parkinson's disease.[23,35,61,76,104,105,155–163] Lin et al. developed a neural network model for the early detection of Parkinson's disease that utilizes motion data collected by IMU sensors to identify individuals with Parkinson's disease and their disease stages. The motion data of patients with Parkinson's disease is highly complex and dynamic, exhibiting irregular gait and asymmetrical arm swing. While similar characteristics can be observed in healthy elderly individuals, they are present to a lesser extent. Neural networks can learn these intricate patterns through their multi-layer structures, automatically identifying key features that differentiate Parkinson's disease from normal aging. Additionally, data collected by IMU sensors includes acceleration and angular velocity information across multiple axes. Neural networks can effectively process this high-dimensional data, reducing its dimensionality through convolution and pooling layers while preserving important characteristic information. The developed neural network model can detect advanced-stage Parkinson's disease patients with an average accuracy of 92.72% and distinguish early-stage Parkinson's disease patients from healthy elderly individuals with an accuracy of 99.67%. This provides an effective technical means for the early diagnosis of Parkinson's disease and monitoring of disease severity.[164] Hsieh et al. proposed a machine learning algorithm based on a single wearable inertial sensor capable of automatically identifying five stages in the fall process: pre-fall, free-fall, impact, rest, and recovery. Various machine learning algorithms have been explored, including SVM, k-nearest neighbor (KNN), naive Bayes (NB), decision tree (DT), and adaptive boosting (AdaBoost). These algorithms effectively manage the high dimensionality, high frequency, and complex temporal characteristics of inertial sensor data. For instance, SVM and AdaBoost are adept at handling nonlinear relationships, KNN and NB address the complexities of data distribution, while DT offers easily interpretable classification rules. The KNN algorithm demonstrated the best performance in the experiments, achieving a sensitivity of 82.17% and an accuracy of 90.28%. It is anticipated to offer detailed information on fall stages for clinical measurement and evaluation, as well as a new approach for early warning of falls in Parkinson's disease and other conditions.[165]

In addition, integrating data from multiple sensors using AI algorithms can more comprehensively capture the characteristic information of the target object, improve the system's recognition accuracy and robustness, and thus expand the application scope while enhancing the user experience.[33,88,94,127,166–169] Yang et al. developed a glove based on triboelectric inertial

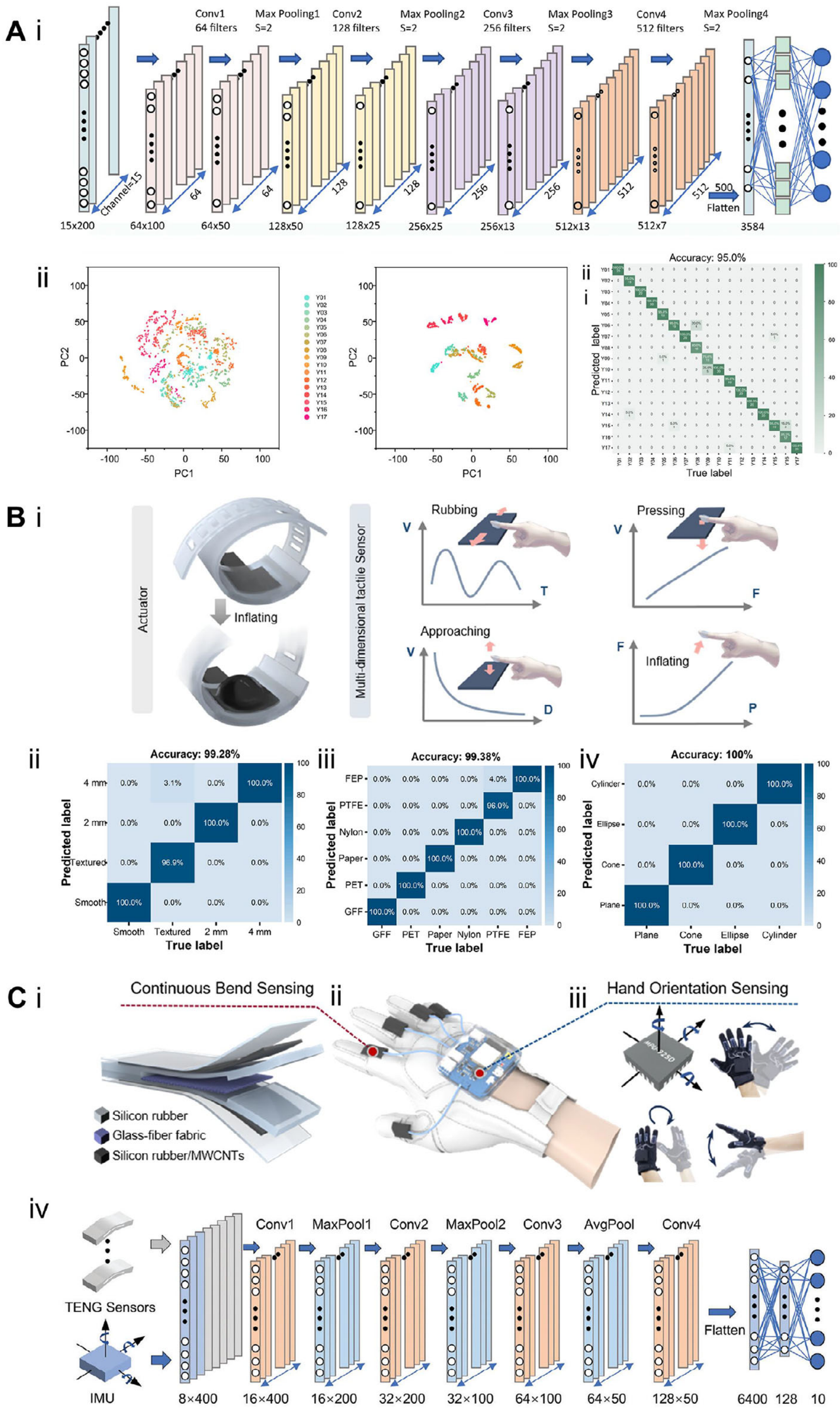

Figure 5. Wearable monitoring of mechanical and physiological signals using an AI algorithm. A) i. The final structure of the optimized CNN for sign language word and sentence recognition. ii. Clustering results of sentence signals from the input and output layers of the CNN. iii. Confusion matrix identifying 17 sentences. Reproduced with permission.[128] Copyright 2025, Springer Nature Ltd. B) i. The TSPF-Ring features actuation and multi-dimensional tactile information sensing capabilities. ii. Confusion matrix for texture recognition. iii. Confusion matrix for material recognition. iv. Confusion matrix for the recognition of four approaching surface shapes. Reproduced with permission.[154] Copyright 2024, Elsevier Ltd. C) The intelligent system of the TI-Glove features triboelectric-inertial dual-mode sensing. i. The detailed structure of the flexible triboelectric-based sensor. ii. Overall structure of the TI-glove. iii. Hand orientation sensing achieved by IMU. iv. Schematic diagram of the overall structure of CNN. Reproduced with permission.[170] Copyright 2024, Wiley-VCH GmbH.

dual-mode sensing (TI-Glove) for human-computer interaction. The glove integrates five triboelectric sensors to detect finger bending motion and an IMU to capture hand posture. The innovative charge-holding circuit effectively addresses the issue of output charge attenuation in the triboelectric sensor, enabling accurate measurement of continuous signals. The system employs CNN for gesture recognition, enabling it to process multi-channel data, such as signals from triboelectric sensors and IMU data. This integration enhances the utilization of information from various sensors, leading to improved accuracy and robustness in gesture recognition. Additionally, during training, the CNN learns the common characteristics of different gesture samples, demonstrating strong generalization capabilities. As a result, it maintains effective recognition even for new and previously unseen gestures. The system excels in recognizing complex sign language, achieving an impressive accuracy of 99.38% (Figure 5C). The system also shows a variety of applications, including complex robot control, virtual reality interaction, and smart home lighting adjustment, which provides a valuable reference for the development of multi-functional human-computer interaction and sign language recognition systems in the future.[170] Bai et al. proposed a novel neural network architecture called SWCTNet for predicting muscle activation and motor dynamics using IMU and sEMG data. SWCTNet cleverly combines CNN and the attention mechanism of Transformers. The CNN extracts local features using convolutional layers, leveraging local connections and weight sharing to efficiently capture local temporal characteristics in the data. In contrast, the Transformer employs a self-attention mechanism that processes sequential data and captures long-range dependencies. Its channel-time attention mechanism enables the model to focus on complex interactions between different time points and muscle signals. Additionally, SWCTNet processes multi-channel data from various IMU sensors and sEMG electrodes. This multimodal data fusion, along with the model's capability to handle nonlinear and high-dimensional data, allows SWCTNet to capture both the details of the signal and the overall trend, ultimately enhancing prediction accuracy. Experimental results indicate that SWCTNet achieves recognition accuracy between 87.93% and 91.03% on public datasets and 98% on self-collected datasets, facilitating the extraction of musculoskeletal features from IMU data and paving the way for real-time monitoring and personalized rehabilitation in home settings. This advancement further enhances the capabilities of IMU-based wearable devices.[171]

In summary, the integration of mechanical physiological signal monitoring with AI algorithms has advanced the development of wearable devices, enhancing their intelligence and precision. Breakthroughs in advanced sensing technology allow these devices to capture a wide range of mechanical physiological signals—from subtle pulses to large movements—without interference. Meanwhile, the implementation of AI algorithms significantly boosts the accuracy of complex classification and prediction tasks. However, several challenges remain in practical applications. Firstly, the signals gathered by sensors tend to drift over prolonged use, which may stem from changes in the physical and material properties of the sensors over time. Environmental factors such as temperature and humidity can degrade the performance of sensitive components, while the aging and wear of electronic parts may cause deviations in the collected signals. This instability affects data accuracy and complicates the analysis performed by subsequent AI models. A recent study introduced a flexible gesture sensor featuring a biomimetic spider silk core-shell structure, utilizing spandex fiber as the core and water-based polyurethane as the shell. The sensitive material, graphene/carbon nanotubes, is securely bonded to the core-shell structure, enhancing stability and durability during long-term use and effectively reducing sensor signal drift.[172] Secondly, individual variations in movement patterns—such as differences in muscle strength, joint range of motion, and exercise habits—pose challenges for AI models. These models struggle to accurately classify and predict physiological signal states using a standardized approach when faced with different individuals. When trained on a specific individual or dataset, the model may become less applicable to new individuals with differing movement patterns, resulting in increased classification errors and decreased prediction accuracy. This limitation hinders the model's effectiveness in practical, widespread scenarios. Recent research has developed a speech recognition and interaction system based on a wearable wireless flexible skin-attached acoustic sensor (SAAS), which uses pre-trained residual neural networks as the starting point for transfer learning. The system utilizes the general features learned by the pre-trained model on other speech recognition tasks and fine-tunes the speech signal features of different individuals to improve the model's generalization ability to various individuals and scenarios.[120] Moreover, the lack of interpretability in AI models remains a significant concern. Complex models, such as deep neural networks, are often viewed as "black boxes," making their decision-making processes difficult to comprehend. In high-stakes fields like healthcare, both doctors and patients are often reluctant to trust decisions that lack clear explanations. This challenge not only impedes the adoption of clinical applications but also restricts researchers from optimizing and improving models due to an inability to pinpoint the basis and potential issues within model decisions. A recent study on dual-mode wearable systems for monitoring lower extremity muscle activity employed the t-distributed stochastic neighbor embedding (t-SNE) algorithm to visualize the extracted features. This approach effectively displayed the distribution and clustering of feature vectors from different sensing modes within the machine learning space, enhancing the transparency and interpretability of the model's decisions.[173] Future research should focus on these areas to fully harness the advantages and potential of AI, facilitating the transition of wearable devices from the laboratory into everyday life.

2.3. AI-Enhanced Chemical Physiological Signal Monitoring

Chemical physiological signals refer to measurable biochemical components in body fluids that reflect the physiological state of the human body. These include electrolytes, metabolites, and various biomarkers, which can be collected and analyzed from fluids such as sweat, saliva, tears, blood, or skin interstitial fluid.[174,175] Wearable chemical sensors, also known as wearable biosensors, typically integrate specific recognition elements—such as enzymes, electrodes, or antibodies[174]—that react specifically with target analytes (like glucose,[176] electrolytes, and lactic acid) and convert them into quantifiable electrochemical signals.[177,178] These sensors are primarily used to detect chemical components in sweat, tears, saliva, or skin interstitial fluid non-invasively,[107,179–181] facilitating the dynamic assessment of human metabolic status, physiological load, or disease-related indicators. For instance, a continuous glucose monitoring (CGM) sensor can measure glucose concentration every few minutes by inserting a micro-probe into subcutaneous tissue fluid,[182,183] enabling diabetic patients to monitor glucose levels throughout the day and adjust their medication accordingly.[176]

The flexible microfluidic sweat sensor patch can accurately collect trace amounts of sweat and analyze lactic acid, pH,[37] and electrolytes (such as sodium and potassium)[184] in real-time using electrochemical or optical methods. This capability is essential for evaluating metabolic levels, electrolyte balance, and fatigue states during exercise.[185] Biosensing elements embedded in smart contact lenses[186] allow for continuous monitoring of tear glucose concentration or intraocular pressure, offering a non-invasive approach to diabetes management or glaucoma screening. Additionally, wearable sensors can detect volatile organic compounds (VOCs) or alcohol released by the skin,[187,188] which can help assess individual metabolic levels or monitor drinking behavior.

In the process of chemical sensing from body fluids, biometric components (such as enzymes and electrochemical electrodes) must be integrated into a flexible wearable platform. However, their stability and long-term reliability under complex environmental conditions—such as temperature fluctuations, biological contamination, and variations in sweat composition—remain significant technical challenges to overcome.[180,189,190] Moreover, individual differences, ambient temperature, humidity, and other factors[191] can significantly impact signal output, necessitating signal processing algorithms that achieve adaptive calibration and robust extraction to ensure accurate and effective biochemical parameters.

To fundamentally address these stability issues, relying solely on sensor hardware improvements may not be sufficient. AI-driven adaptive calibration models, leveraging real-time compensation for sensor aging, environmental variability, and individual physiological differences, could provide a more flexible and effective solution. Recent studies have demonstrated successful implementation of implantable biosensors for direct in vivo chemical signal monitoring. Cohen et al. developed a nanotube-based optical sensor embedded in tissue that detects molecular changes via near-infrared fluorescence, enabling minimally invasive, long-term monitoring of metabolic variations.[192] Similarly, Chen et al. introduced a barcode-based multiplexed implant capable of simultaneously tracking glucose and oxygen levels in subcutaneous tissue.[193] Their system incorporates AI-driven calibration to correct for tissue scattering and temperature shifts, showing stable performance during free movement in animal models.

However, significant limitations exist in human chemical and physiological signal data for practical monitoring applications. The complexity of human physiology and lifestyle factors—such as diet, medication, and mental stress—can lead to substantial changes in body fluid composition, thereby reducing the stability and repeatability of monitoring results. Additionally, sensor characteristics—such as material aging, response lag, and drift—can negatively impact the accuracy of long-term monitoring, affecting clinical outcomes. To address these issues, future research should focus on developing high-performance materials and exploring new sensing mechanisms. Optimizing the structural design and manufacturing process of sensors is essential to enhance their stability and resistance to interference. Concurrently, advanced signal processing methods and AI algorithms should be integrated to enable real-time calibration and error correction of data, improving monitoring accuracy and robustness. Besides hardware optimization, future breakthroughs in intelligent sensing systems will heavily rely on deeper integration of AI. Leveraging big data analytics and deep learning enables real-time sensor calibration and adaptive corrections, significantly enhancing long-term monitoring accuracy. Furthermore, multimodal data fusion through AI substantially improves the predictive sensitivity of health monitoring systems, transforming monitoring from passive observation to proactive diagnosis.

AI technology is primarily manifested in two aspects within this field. First, machine learning is employed for original signal calibration and pattern recognition, effectively removing noise and enhancing the accuracy of analyte detection.[37,194–197] Zhou et al. developed a microsystem that integrates multi-mode sensors and AI algorithms, significantly improving the detection accuracy of glucose, lactic acid, and electrolytes in sweat.[37] Second, multiple biochemical indicators are integrated with other physiological signals to predict and comprehensively evaluate health status using deep learning models. Muthu et al.[38] proposed an in vitro wearable system capable of real-time collection of multi-modal data, such as heart rate and sweat composition, while combining the Internet of Things with AI algorithms for personalized health monitoring and disease early warning.[19] Notably, the Apta sensor module, in conjunction with the Boltzmann Belief Network and Genome-Wide Association Studies (GWAS) method, achieved early prediction of colorectal cancer, boasting a model accuracy of 96.33% and sensitivity of 92.33%. Moreover, the glucose module is jointly analyzed by the neural fuzzy system (GARIC) and the deep learning model to assist in identifying health risks related to abnormal glucose metabolism. It is worth noting that the typical research cases of AI applications mentioned above reflect a clear common trend, that is, the use of AI technology to achieve mutual calibration and fusion analysis between multi-dimensional signals. In future research, establishing a complete AI-driven link from the detection of a single biomarker to the collaborative analysis of multiple physiological parameters will greatly enhance the practicality and reliability of physiological signal monitoring technology in clinical practice and personal health management.

In summary, AI-enabled wearable chemical sensors hold the potential to overcome the limitations of single-indicator monitoring, providing richer information for predicting the physiological state of the human body and achieving multi-parameter integrated analysis. This advancement offers robust technical support for personalized medicine and predictive health management. However, current research in this area remains relatively limited, highlighting the urgent need to promote deeper application in wearable intelligent devices.

2.4. AI-Enhanced Thermophysiological Signal Monitoring

Thermophysiological signals primarily refer to human body temperature and its dynamic changes, which are important vital signs reflecting metabolic activity, immune state, and neuroregulatory function.[198] Traditional temperature measurement methods, such as armpit or oral thermometers, provide static single-point measurements that fail to capture trends in temperature fluctuations. In contrast, wearable temperature sensors enable continuous, non-invasive, and multi-modal body temperature monitoring, offering a new approach for individualized health management and disease prediction.[15,199–202]

According to their sensing mechanism, wearable and implantable temperature sensors can generally be divided into five categories: resistive sensors achieve signal conversion through changes in material resistance with temperature, which is suitable for daily monitoring such as skin attachment; thermoelectric sensors drive voltage based on temperature difference, which is suitable for short-term high temperature or capsule-like scenarios; infrared sensors use human radiation energy for non-contact temperature measurement, which is suitable for long-distance screening but is greatly affected by environmental interference; fiber optic sensors rely on spectral response, have anti-electromagnetic interference capabilities, and can be used in special environments such as Magnetic Resonance Imaging (MRI); injectable/degradable devices are delivered through microneedles, adhere to the tissue surface, and support deep dynamic temperature monitoring. These categories have their own advantages in terms of measurement methods, application sites, and integration characteristics.[203] Currently, AI-driven research on thermophysiological signals remains limited, mainly due to sparse, low-resolution datasets and the subtle, slow-changing nature of temperature signals. Nevertheless, combining thermal sensing with AI—especially through multimodal fusion—offers promising potential for personalized health monitoring, improved signal interpretation, and adaptive correction of environmental noise in wearable systems.

Recent work on injectable flexible implants has opened a complementary route for monitoring deep-tissue temperature (ICT) together with intracranial pressure (ICP) and cortical activity (ECoG). These devices deploy stretchable or bio-resorbable polymer/metal nanomembranes that can be delivered through a minimally invasive syringe and unfold to conform the brain surface. Oh et al. demonstrated an RF-powered injectable platform that logs ECoG and intracranial temperature simultaneously while supporting closed-loop neuromodulation;[204] Yu et al. reported a degradable ECoG-ICP composite electrode that remains stable for weeks after sub-dural injection;[205] Kim et al. reviewed material strategies for multimodal injectable chips that couple temperature, pressure and electrical sensing in vivo[206]; Ashammakhi et al. and Lee et al. introduced the concepts of "biodegradable electronics" and "electronic drugs," highlighting syringe-deployable sensors for ICP-ICT co-monitoring in traumatic brain injury;[207,208] Cho et al. further detailed nanomembrane-based injectable thermistors integrated with high-resolution ECoG arrays for neuro-thermal coupling studies.[209] Collectively, these "inject-and-unfold" systems point to a future in which AI-driven, multimodal implants deliver personalized brain-temperature and pressure surveillance alongside electrophysiology.

In recent years, researchers have integrated micro-thermal elements—such as thermistors, thermocouples, and infrared sensors—into smart wristbands, skin patches, or underwear to track skin surface temperature in real time. This allows for observation of body temperature fluctuations caused by circadian rhythms, emotions, or exercise.[185,210–214] Some devices are designed to be attached to the armpit, behind the ear, or other areas close to the core body temperature, enabling more accurate monitoring of fever trends and assisting in the early warning of infectious diseases or the evaluation of treatment efficacy.[215] Zhang et al. developed a wearable ear canal thermal sensor that can track core body temperature with high precision, aiding in heat stroke early warning and fever trend analysis.[216]

In the field of women's health, accurately monitoring basal body temperature can predict ovulation, which is beneficial for fertility planning and hormone cycle management.[217,218] Additionally, for individuals in high-temperature environments, such as workers or athletes, wearable temperature sensors can identify the risk of heat stress in real time,[219] preventing serious consequences like heat stroke.

At the technical level, this type of sensor commonly employs temperature-sensitive elements such as thermistors and infrared thermal imaging,[111] which offer good sensitivity and flexible integration capabilities. Since sweat evaporation and changes in ambient temperature can influence skin temperature readings, environmental sensors and algorithms are often combined for calibration in practical applications, helping to estimate a value closer to the true core temperature.

However, there are significant limitations regarding human thermophysiological signal data and sensor characteristics. First, skin surface temperature is heavily influenced by ambient temperature, humidity, local sweating, and airflow, causing measurement errors and data drift. Addressing these errors solely through hardware optimization is challenging, highlighting the importance of employing AI algorithms to dynamically correct environmental interference, significantly enhancing measurement accuracy and reliability. Such integration of environmental parameters and AI calibration represents a promising direction for next-generation intelligent temperature monitoring technologies. Second, while some devices are positioned closer to the core body temperature, it remains challenging to entirely eliminate systematic errors and individual differences in measurements, resulting in insufficient reliability and universality of the data. Additionally, the long-term stability of sensor materials and structures, as well as wearing comfort and safety on the skin, are critical issues that must be addressed. Future research indicates that optimizing sensor materials and design structures, along with advanced multi-sensor fusion and AI algorithms, should enhance the real-time calibration capabilities of temperature signals and improve the accuracy of anomaly recognition. From a long-term development perspective, simple hardware optimization cannot completely solve the problems of individual differences and systematic errors, and the deep integration of AI provides greater potential. Specifically, in the future, we can make full use of the adaptive characteristics of AI models to reduce systematic errors in different populations and environments through individualized modeling and real-time learning, thereby achieving personalized and accurate temperature monitoring and health risk warning. Furthermore, more extensive, multi-scenario clinical application studies should be conducted to verify and optimize the reliability and practicality of existing monitoring systems.

Although the temperature signal itself is relatively intuitive, AI technology demonstrates significant potential in this field. By analyzing the relationship between body temperature and other physiological parameters (such as heart rate and physical activity) through machine learning models, the accuracy of abnormal fever detection can be improved, temperature trends can be predicted, and intelligent assessments of disease status can be achieved. Liang et al.[39] collected skin surface temperature (Ts) and thermal conductivity layer temperature (Te) using wearable dual temperature sensors and developed a machine learning model for predicting human core body temperature (Tc). By incorporating eight features, including initial temperature, square term, and first-order difference, they studied and compared the performance of six common algorithms. Ultimately, the linear regression model (LR) was selected as the optimal solution. The model showed promising results in ten subjects, with a mean absolute error (MAE) of 0.15 ± 0.04 °C, a root mean square error (RMSE) of 0.17 ± 0.05 °C, and a mean relative error (MAPE) of 0.40 ± 0.12%. A prediction accuracy of less than 0.3 °C was achieved in 100% of the subjects, demonstrating the system's robustness and potential for practical application in various states. During public health events, such as the novel coronavirus epidemic, temperature monitoring systems that combine wearable devices and AI algorithms have been used for real-time screening and geographical tracking of individuals with fever, aiding in the early warning and prevention of infectious diseases. Wahid et al. proposed the COVICT framework, an IoT + AI system that integrates temperature, heart rate, and geographic information for COVID-19 fever identification and location.[220] Ali et al. developed a machine learning-based early recognition system for COVID-19, utilizing wearable nodes (including temperature sensors) to gather continuous data.[40] Sheth et al. suggested that the AI + IoT system integrates multi-mode signals such as heart rate, body temperature, and SpO_2 to predict symptoms, making it suitable for epidemic prevention, control, and intelligent medical treatment.[221] These studies demonstrate a consistent trend of integrating AI with multimodal physiological data and geographic information, highlighting the potential of AI-driven thermophysiological monitoring in advancing personalized healthcare and public health management.

In summary, although the measurement of human thermal physiological signals is relatively direct, the challenge of interference from environmental and individual factors is still prominent. The integration of AI technology provides an important breakthrough in this field: through adaptive correction of environmental factors, multimodal signal fusion and personalized modeling, it is expected to solve the problems of insufficient accuracy and low stability of existing monitoring methods. In the future, we should further promote the deep integration of AI and thermal physiological signal monitoring technology to enhance its practical application capabilities in the fields of personalized health management and public health prevention and control. To provide a clearer summary of the application of AI technologies in various types of wearable physiological signal sensors, **Table 1** presents an overview of different sensor types, corresponding algorithm types, application areas, performance metrics, as well as future challenges and prospects.

3. Current Challenges, Technological Advantages, and Future Trends

3.1. Data Privacy and Security

Data privacy and security are critical concerns for wearable health devices. These devices continuously collect highly sensitive personal physiological data, such as heart rate, activity trajectory, and sleep duration, which can lead to privacy violations and security risks if leaked. Currently, most wearable sensors transmit data to the user's smartphone or a cloud server for storage and analysis, introducing multiple security vulnerabilities. For instance, wearable devices often connect to mobile phones via Bluetooth, NFC, or Wi-Fi, and without encryption and authentication mechanisms, hackers can intercept or tamper with data through these wireless links.[47] In addition, many health applications are developed and hosted by third parties, which increases the amount of data stored by third parties,[48,49,58] Users grant these third parties access to their wearable device data, heightening the potential for misuse.

Addressing these challenges requires efforts at both the system architecture and algorithm levels. On one hand, technical measures such as end-to-end data encryption, hierarchical authorization, and anonymization should be implemented to ensure the confidentiality and integrity of user data throughout the entire process of collection, transmission, and storage. On the other hand, AI technology can enhance privacy protection, for example, through abnormal behavior detection via machine learning and timely identification of unauthorized access or signs of data breaches. Distributed AI models, such as federated learning, allow for model training without centralizing original data, thereby reducing the likelihood of sensitive data leakage. Chen et al. proposed a federated learning framework that achieves superior average classification accuracy, outperforming the best baseline methods by 21.6% and 16.8% on two Parkinson's disease datasets. It also achieves the highest classification accuracy and mean F1-score across almost all users, substantially narrowing the gap with the ideal centralized scenario. These results demonstrate that federated transfer learning enables effective symptom classification in real-world applications.[156]

Importantly, users are more likely to continue using wearable health devices and sharing their data when they believe their privacy is safeguarded.[56] Therefore, establishing robust data security mechanisms and regulations is essential for promoting the widespread adoption of wearable sensor technology. It should be pointed out that different studies differ in terms of sensor type, data set size, preprocessing process, hardware platform, and model implementation, making it difficult to strictly compare performance indicators such as accuracy, inference latency, and energy consumption. In the future, it is necessary to conduct a systematic evaluation of the comprehensive performance of various algorithms under a unified benchmark and test environment.

3.2. Energy Consumption and Battery Life

Energy consumption limitations and battery life present significant challenges for wearables in long-term continuous

Table 1. Summary of AI applications in wearable sensor research.

Sensor type	Number of sensing modalities	Number of channels	Algorithm type	Application areas	Dataset source	Performance	Challenges and prospects	Refs.
Single-Walled Carbon Nanotube Strain Sensors	2	5	CNN, SNN	Gesture recognition	Self-built dataset	High recognition accuracy in 600 samples (100%); Error rate in dark environments (3.3%)	Enhance robustness to noise/illumination; Expand sensing modalities	[125]
piezoresistive film + conductive wire	1	548	CNN, ResNet-18 variants	Object recognition, weight estimation, gesture analysis	Self-built dataset	Recognition accuracy of 26 objects (100%); Classification of 7 gestures (89.4%); Weight estimation error (56.88 g)	Optimize temporal information processing; Enable complex human-computer interaction tasks	[126]
ECG sensor	1	1	CatBoost machine learning classification algorithm	Atrial Fibrillation Detection	AFDB-2017, MITBIH-AFDB	High sensitivity (99.61%), specificity (99.64%), accuracy in testing set (99.62%)	Improve real-time processing; Reduce false detection; Enhance signal quality assessment	[86]
ECG sensor, accelerometer	2	3	RNN, LSTM	Atrial fibrillation detection, syncope detection	MIT-BIH Arrhythmia Database	Training dataset(98.89%) Test data (97.23%) Overall accuracy(97.61%)	Enhance algorithm robustness; Reduce false alarms; Optimize real-time data processing	[87]
chest-worn breathing belt + triaxial accelerometer	2	4	LSTM + threshold method	Breathing pattern monitoring, human activity recognition	Self-built dataset	Average accuracy in testing dataset (97.22%); Prediction time (0.0094s)	Improve complex activity recognition; Enhance real-time monitoring accuracy	[116]
sEMG sensor	1	64	Hyperdimensional Computing	Gesture recognition	Self-built dataset	Basic gestures (97.12%) Molti-DOF gestures (92.87%); Post-update recovery (9.5%)	Adapt to sensor position/environmental changes; Optimize computational efficiency/energy consumption	[99]
thin film pressure sensor + bending sensor + IMU	3	11	EWA, K-Means clustering, BPNN	Parkinson's Disease Assessment	Self-built dataset	Tremor classification accuracy in test sets (95.83%); Kappa consistency (0.937); ICC reliability (>0.9)	Improve gesture recognition accuracy; Optimize sensor position impact	[112]
thin film ECG electrodes + IMU sensors	2	4	CNN, ResNet, R-peak Detection	ECG monitoring, arrhythmia detection,	PTB Diagnostic ECG Database, INCART Arrhythmia Database	ECG classification accuracy (98.7±1.4%); Motion classification accuracy (98.9±3.3%)	Enhance model generalization; Improve real-time stability; Expand medical applications	[127]

(*Continued*)

Table 1. (Continued)

Sensor type	Number of sensing modalities	Number of channels	Algorithm type	Application areas	Dataset source	Performance	Challenges and prospects	Refs.
ECG Sensor	1	1	CNN + LSTM + Attention Mechanism	atrial fibrillation detection, abnormal rhythm detection	MIT-BIH Arrhythmia Database	Classification accuracy in database (98.95%); Sensitivity (96.54%); Specificity (99.38%)	Optimize time-series feature extraction; Improve model generalization; Extend to periodic physiological signals	[83]
Accelerometer + Gyroscope	1	6	SVM, kNN, NB, DT, AdaBoost	Fall detection	Self-built dataset	kNN sensitivity (82.17%); Precision (85.74%); Accuracy in testing set (90.28%)	Optimize free-fall phase detection; Improve time window selection; Enhance real-time/generalization	[165]
Electrocardiogram	1	2	1D-CNN + Autoencoder + Transfer Learning + Grad-CAM Explanatory Module	Smart healthcare, arrhythmia detection	MIT-BIH Arrhythmia Database	Accuracy in database (98.9% clean data; 94.5% noisy data)	Reduce FL communication costs; Strengthen privacy; Enhance heterogeneous device generalization	[85]
Electrocardiogram	1	12	SVM, kNN, GBDT, RF + MPA	Smart healthcare, arrhythmia detection	MIT-BIH, EDB, INCART	Highest accuracy in test set (99.67% MIT-BIH; 99.92% EDB).	Optimize computational efficiency; Combine deep learning with metaheuristic algorithms	[84]

monitoring. Due to the small size of wearable sensors, their built-in battery capacity is limited, and the continuous collection and wireless transmission of physiological signals consume considerable power. Consequently, extending the device's operating time has become a critical issue. This challenge is exacerbated by the introduction of AI for real-time analysis, which adds to the device's energy demands. For instance, continuous physiological monitoring (e.g., ECG, sleep) and real-time communication can significantly increase power consumption, while the integration of AI inference and local processing further burdens the battery, particularly in compact devices.[222] This situation is not conducive to long-term use.

To address these challenges, the first step is to implement low-power design strategies. This includes utilizing ultra-low power sensor chips and communication modules, adapting sampling rates and transmission frequencies based on context (such as reducing data upload frequency during rest),[223] and opting for on-device processing instead of cloud analysis to minimize wireless transmission. Additionally, the development of new batteries and energy harvesting technologies offers innovative solutions for powering wearable devices. For example, flexible lithium and solid-state batteries can be safely integrated into bendable devices without compromising capacity.[224] Energy harvesting technologies aim to derive energy from the environment or the human body, such as using thermoelectric materials to convert temperature differences into electricity,[225] or employing piezoelectric and electromagnetic devices to capture energy from human movement.[226–229] Embedding nanogenerators into smart clothing, which harness the wearer's walking and friction to produce electricity, can also help extend the device's battery life.[230] In the future, the development of fully self-powered wearable sensors (without external batteries) is an important direction, as achieving this would completely eliminate battery limitations. Enhancing the self-powered durability of wearable TENGs remains a major challenge in the field. Guan et al. developed a woven-structured triboelectric nanogenerator (WS-TENG) with excellent durability and washability. After 20 000 continuous contact-separation cycles, the electrical output of the WS-TENG remained stable without noticeable degradation. Moreover, output voltage signals after five washing cycles demonstrated that nearly 90% of the initial performance could be well retained, confirming the robustness of the WS-TENG under repeated mechanical and washing stresses.[231] Furthermore, AI algorithms can contribute to power management by using intelligent predictive models to optimize the sensor's work/sleep modes, maximizing energy savings while ensuring that critical events are not missed.[232] Overall, enhancing energy efficiency and endurance requires collaborative innovation across multiple disciplines, including materials, electronics, and algorithms, which is a crucial step in transitioning wearables from lab prototypes to everyday applications.

3.3. Standardization and Compatibility

With the continuous evolution of wearable sensing technology, the issues of data standardization and system interoperability have become increasingly prominent. Different devices often utilize proprietary data formats and communication protocols, making data integration challenging and limiting the ability to analyze multi-source physiological information. Simultaneous recording of multiple physiological signals, such as ECG and gait),[233] is difficult to achieve, as is their joint interpretation. To address this issue, researchers are advocating for the development of uniform data formats, interface protocols, and compatibility standards to enhance data consistency and exchangeability. The Generic Attribute Profile (GATT) service definition in the Bluetooth Low Energy (BLE) protocol has enabled cross-brand data reading in some devices, providing an initial technical foundation for interoperability.[234] Additionally, as the application of AI models in health monitoring continues to expand, the importance of data consistency and scale is further underscored. Achieving a unified data format among devices is essential for supporting multi-source training, generalized modeling, and cross-device deployment of AI systems. Therefore, promoting the collaborative evolution of data standards and interface protocols is a crucial technological pathway for the efficient integration and intelligent analysis of wearable systems.

3.4. Wear Comfort and Long-Term Monitoring Stability

The performance of wearable physiological sensors heavily depends on their wearing comfort and the stability of signal acquisition. High-quality signals typically require the sensor to maintain close contact with the skin; however, a fit that is too tight can lead to irritation or discomfort from compression. To address this challenge, researchers have increasingly utilized flexible electronic devices and biocompatible materials for structural optimization in recent years, enhancing both the wearing experience and signal reliability. Currently, mainstream solutions often employ ultra-thin elastic polymer substrates and stretchable conductive components to achieve a "skin fit" design that accommodates joint motion and minimizes displacement errors.[235] Additionally, hydrogel-like adhesive materials and fabric-embedded structures have been introduced to replace traditional adhesives, thereby reducing the risk of skin reactions during prolonged wear.[236,237]

Nevertheless, several technical bottlenecks persist. On one hand, while flexible materials offer good adhesion, they can suffer from decreased adherence and material fatigue due to contamination from sweat, water vapor, or sebum over extended use, impacting stability. On the other hand, the contact impedance between the flexible electrode and the skin varies over time, which can lead to signal baseline drift or increased noise, particularly in dynamic situations. Although solutions such as automatic baseline calibration, signal anomaly detection, and redundant sensor deployment mechanisms have been proposed to enhance robustness, these approaches often involve trade-offs between low power consumption, real-time performance, and algorithm complexity.[238] Furthermore, the absence of a standardized skin-device interface model limits the system's adaptability to various application scenarios.

In summary, the collaborative advancement of flexible material design, improvements in adhesion mechanisms, and adaptive algorithms forms the core technology pathway to enhance the long-term monitoring capabilities of wearable physiological sensors. However, widespread deployment still requires

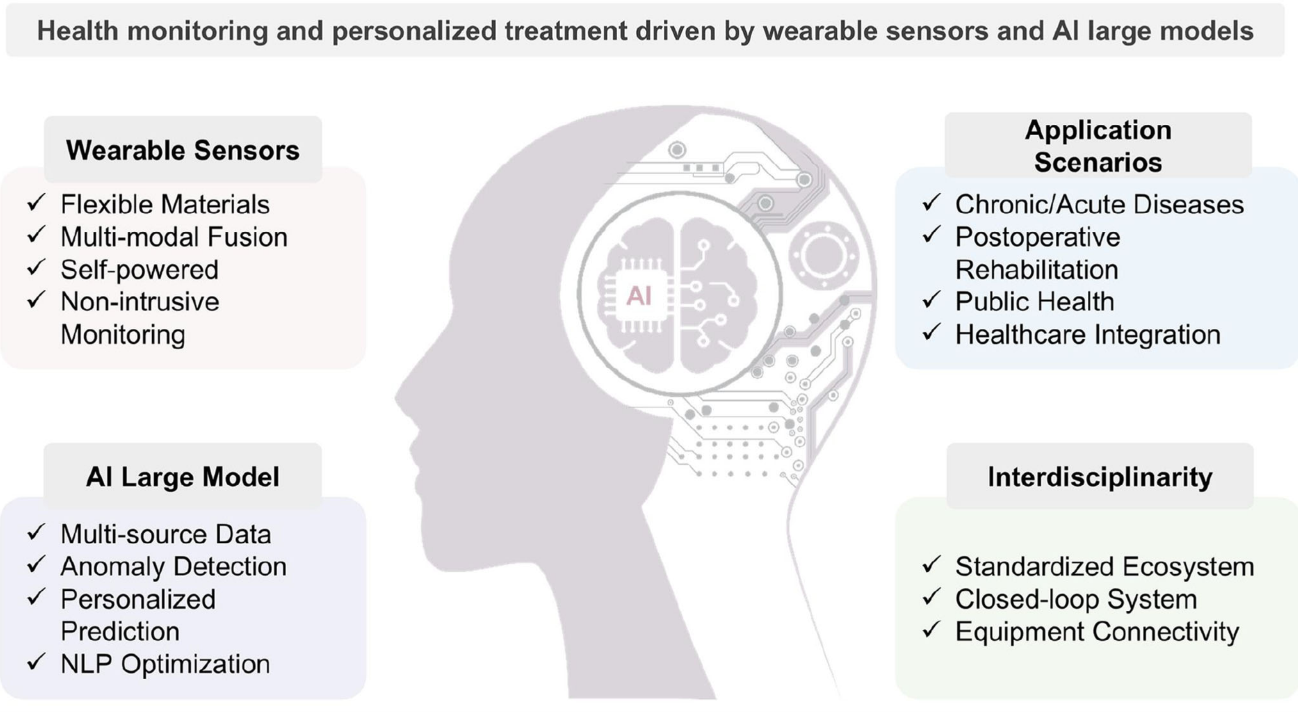

Figure 6. Health monitoring and personalized treatment driven by wearable sensors and AI large models.

addressing critical issues such as material durability, signal fluctuations, and structural integration.

3.5. Telemedicine and Personalized Health Management

The integration of wearable sensors with telemedicine platforms is transforming healthcare systems from intermittent visits to continuous health monitoring and individualized interventions. The Remote Patient Monitoring (RPM) system, utilizing multi-parameter physiological sensors (such as ECG, SpO_2, blood pressure, and blood sugar), enables real-time collection, analysis, and feedback of vital signs outside of hospital settings. This system is essential for managing chronic diseases, postoperative rehabilitation, and elderly care, providing long-term continuous support.[70,239] When monitoring data deviates from an individual's baseline or preset threshold, the system can automatically trigger alarms to assist doctors in early intervention, significantly reducing the incidence of acute events.

The continuous collection of time-series physiological data also provides a foundation for AI algorithms, supporting functions such as disease risk trend prediction, treatment response evaluation, and health behavior recommendations. Compared to traditional single measurements during return visits, continuous monitoring more accurately captures fluctuations in physiological states and enhances the adaptability and timeliness of interventions. Additionally, the platform integrates an adaptive feedback mechanism based on personal historical data, promoting active patient participation in disease management.

At the system level, monitoring data can be seamlessly connected to electronic health records (EHR) and clinical decision support systems (CDSS),[70] facilitating data connectivity both inside and outside the hospital. This connection closes the loop between remote monitoring, physician evaluation, and intervention recommendations. The architecture has been preliminarily validated in managing diseases such as heart failure, diabetes, and chronic obstructive pulmonary disease (COPD), and has the potential to expand into postoperative rehabilitation, elderly home care, and public health monitoring.

3.6. Future Development Trend

Looking ahead, AI-enabled wearable physiological signal monitoring will rapidly advance in technology and application, further maturing and improving through the support of policy, market forces, and interdisciplinary collaboration (**Figure 6**).

Direction of Technological Innovation: In the future, wearable physiological signal monitoring systems will evolve across multiple dimensions, including materials, devices, computation, and modeling. New flexible materials, such as conductive hydrogels, electronic skin, and smart fabrics, will enhance sensors' flexibility, biocompatibility, and mechanical deformation resistance, allowing for "non-inductive" attachment to skin and fabric surfaces. This will enable adaptation to joint movements and dynamic surface changes. Multi-modal fusion will become increasingly prevalent, allowing a single device to simultaneously collect ECG, skin temperature, myoelectric signals, sweat components, and other data, thereby providing a richer physiological basis for health state modeling. In terms of energy, self-generating technologies such as triboelectric nanogenerators, flexible solar cells, and biofuel cells will enhance the independent operation capabilities of wearable devices, reducing reliance on battery replacement and charging. This is expected to lead to a closed-loop system of "continuous monitoring – continuous energy supply," improving availability and user experience. Additionally, rapid advances in smart chips and edge computing will enable complex AI reasoning to occur on local devices. Low-power neural network acceleration chips will be integrated into wearable platforms, facilitating real-time detection and local feedback on physiological abnormalities, such as arrhythmias and falls. This will reduce latency, conserve bandwidth, and enhance data security.

Notably, the emergence of large-scale pre-trained foundation models—such as DeepSeek, GPT-4 and Gemini—has opened new avenues for intelligent wearable health-monitoring systems; however, their capacity to process long, high-frequency time-series data remains limited. To overcome this bottleneck, current practice couples these generic language models with specialized temporal encoders (e.g., transformer-based sequence learners or graph neural networks) that extract fine-grained physiological features, while the language model handles cross-modal reasoning and dialogue. Modern multimodal architectures further embed mixture-of-experts (MoE) gating, dynamically routing physiological, textual and visual streams to dedicated expert subnetworks, thereby improving efficiency and accuracy when data modalities fluctuate over time. Within such a hybrid framework, transfer learning, anomaly detection and individualized trend modeling can be achieved with only modest labeled datasets. DeepSeek, for instance, first maps raw signal segments into compact embeddings via a learnable temporal expert before the language model converts them into context-aware health summaries that support personalized intervention. The conversational interface generated by the language model then explains health trajectories and suggests lifestyle adjustments in plain language, enhancing user comprehension and adherence.

Application Scenario Expansion: With the enhancement of system functions and improvements in algorithm generalization ability, the application boundary of wearable monitoring technology will continue to expand. Currently, it is widely used in chronic disease management, but its future applications will gradually extend into areas such as acute disease early warning, postoperative rehabilitation follow-up, tumor treatment monitoring, and public health alerts. For instance, through remote ECG and blood pressure monitoring, doctors can assess the recovery status of postoperative heart disease patients in real time and adjust medication regimens accordingly. During chemotherapy, devices can record risk signals of complications such as fatigue, fever, and heart rate changes to assist in risk assessment. In infectious disease prevention and control, wearable temperature sensors, cough recognition, and respiratory monitoring systems can track trends in microsymptoms within the population, aiding in the development of early warning mechanisms.

Beyond medical scenarios, fields such as personal health management, sports training, elderly care, and occupational health will also become focal points for wearable sensors. For example, athletes can utilize biochemical sensors to monitor lactate concentration and EMG signals in real time, optimizing their training strategies. In smart elderly care, sensors integrated with smart home systems can monitor vital signs and activity levels continuously. If a fall or abnormal fluctuation is detected, the system will automatically issue an alarm and initiate a care response.

Interdisciplinary Cooperation and Ecological Construction: To achieve these advancements, continuous collaboration among electronic engineering, materials science, embedded systems, AI, and clinical medicine is essential. The wearability of flexible materials, low-power optimization of sensing systems, edge deployment of AI algorithms, and medical interpretation of clinical indicators all require the efforts of cross-disciplinary teams. For instance, developing biocompatible materials necessitates collaboration between materials scientists and electronics engineers. Deploying neural network models requires hardware and software co-design to achieve optimal energy efficiency. Furthermore, standardization systems and platform compatibility mechanisms are crucial for system integration. The standardization of device interface protocols, data representation structures, and privacy compliance mechanisms will determine the efficiency of integrating future wearable systems into medical information systems such as EHR/CDSS, creating a true closed-loop information flow between "devices-doctors-users." In this process, the role of large models will increasingly emerge: models like DeepSeek can serve as core engines for health data understanding and decision support, connecting multi-source data inputs with multidimensional feedback outputs, thus becoming an "intelligent hub" for individual health management systems.

4. Conclusion

Wearable sensor technology has demonstrated significant potential and broad prospects in human physiological signal detection. By integrating multi-modal signals—such as bioelectricity, biomechanics, chemistry, and heat—with AI algorithms, wearable sensors can continuously and accurately monitor physiological indicators like heart rate, body temperature, movement posture, and metabolism. This capability provides crucial support for health status assessment, disease early warning, and personalized medicine. The introduction of intelligent algorithms has greatly enhanced the accuracy of signal processing and pattern recognition, highlighting the value of data-driven diagnostic decisions and health management strategies.

Moreover, the widespread application of this technology helps reduce medical costs, optimize resource allocation, and alleviate pressure on public health systems, yielding significant socioeconomic benefits. However, the large-scale implementation of wearable physiological signal monitoring faces numerous challenges, including data privacy and security, energy consumption and battery life, standardization and compatibility, as well as wearing comfort and long-term stability. Addressing these challenges requires simultaneous innovation at both the system architecture and algorithm levels. On one hand, technologies such as end-to-end encryption and federated learning should be adopted to ensure the security of data collection, transmission, and storage, while low-power design and self-powered technologies should be utilized to extend equipment battery life. On the other hand, a unified standard must be developed to improve the interoperability of equipment and data, alongside enhancements in flexible materials and processes to boost the comfort and long-term stability of sensors, ensuring a positive user experience during extended wear.

Looking ahead, wearable physiological monitoring is expected to adopt a multi-tier model stack rather than relying solely on general-purpose language models. Ensemble strategies that fuse outputs from temporal experts, probabilistic forecasting networks and large language models are becoming the de facto standard, balancing high-resolution signal fidelity with semantic interpretability. MoE gating mechanisms embedded in multimodal backbones dynamically allocate compute to the most relevant expert (vision, text, acoustics, or bio-signal), which is essential for power-constrained edge devices. Supported by clearer regulatory guidance, secure on-device learning, and federated analytics, such hybrid AI pipelines are poised to transition from research prototypes to routine clinical workflows. Consequently, AI-enabled wearables will expand beyond chronic-care scenarios into acute event detection, rehabilitation coaching and population-level early-warning networks, delivering more precise, timely, and explainable health protection.

In summary, despite the challenges and opportunities ahead, if we continue to overcome technical bottlenecks and seize the innovation opportunities presented by AI integration, wearable physiological signal monitoring technology will undoubtedly play a revolutionary role in the future of medical and health fields.

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Conflict of Interest

The authors declare no conflict of interest.

Keywords

artificial intelligence (AI), health monitoring, multimodal data fusion, physiological signals, wearable devices

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