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WEARABLE DEVICES AND AI-DRIVEN PHYSICAL ACTIVITY MONITORING IN PUBLIC HEALTH: IMPLICATIONS FOR CHRONIC DISEASE PREVENTION AND HEALTH EQUITY – A NARRATIVE REVIEW

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ABSTRACT

Background: The escalating global prevalence of non-communicable diseases necessitates proactive epidemiological strategies. Physical inactivity is a primary, modifiable risk factor in the pathogenesis of these chronic conditions. Consequently, digital epidemiology has attracted profound interest, particularly through wearable devices integrated with artificial intelligence (AI), which facilitate the continuous, real-time monitoring of physiological markers.
Aim: This study aims to synthesize current evidence on AI-driven wearable devices in public health, evaluating their biological and behavioral mechanisms in chronic disease prevention, technical modalities, clinical applications, and implications for global health equity.
Methods: A narrative literature review was conducted utilizing PubMed, Scopus, and Web of Science, focusing on peer-reviewed studies published between 2010 and 2026. Eligible publications included observational studies, algorithm validation research, and randomized controlled trials evaluating machine learning and physical activity monitoring.
Results: AI-driven wearables effectively promote disease prevention via early anomaly detection and personalized behavioral interventions. Major modalities - including accelerometry, photoplethysmography (PPG), and continuous glucose monitoring (CGM) - powered by deep learning, demonstrate substantial clinical benefits in managing cardiovascular and metabolic disorders. However, critical limitations remain, including algorithmic bias, data privacy concerns, and the exacerbation of the digital divide.
Conclusions: Wearable devices and AI analytics are highly promising adjuncts in public health surveillance. To realize their full preventative potential, future research and policy must prioritize protocol standardization, algorithmic fairness, and inclusive design to ensure equitable accessibility across diverse demographic groups.

KEYWORDS

Wearable Devices, Artificial Intelligence, Physical Activity Monitoring, Chronic Disease Prevention, Health Equity, Machine Learning

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1. Introduction

The global burden of non-communicable diseases (NCDs), including cardiovascular diseases, type 2 diabetes mellitus, chronic respiratory conditions, and obesity, continues to exert unprecedented pressure on healthcare systems globally [50]. The growing prevalence of these conditions is inevitably linked to behavioral determinants, primarily physical inactivity, which contributes to systemic inflammation, metabolic dysregulation, and a cascade of cardiometabolic pathogenesis [44]. Epidemiological surveillance of physical activity has historically relied upon self-reported questionnaires and diaries; however, these methods are intrinsically flawed, prone to recall bias, social desirability effects, and substantial overestimations of moderate-to-vigorous physical activity (MVPA) [4].

Despite advances in traditional epidemiological methods, the management and prevention of chronic diseases remain challenging because episodic clinical assessments fail to capture the dynamic, daily physiological fluctuations of patients [41]. This temporal gap in patient monitoring has catalyzed a paradigm shift toward digital health and precision medicine, leveraging omnipresent computing to capture continuous physiological data in free-living environments [11]. Within this field, wearable devices integrated with artificial intelligence (AI) and the Internet of Things (IoT) have emerged as powerful orthobiologic and digital therapeutics, transitioning from basic fitness tracking to clinical-grade diagnostic and preventative tools [10].

Modern wearable technologies encapsulate a diverse array of biosensors, including triaxial accelerometers, gyroscopes, photoplethysmography (PPG) sensors, and continuous glucose monitors (CGMs) [32]. When combined with sophisticated machine learning (ML) and deep learning (DL) algorithms, these devices can decode complex human activity, estimate energy expenditure with high granularity, and detect subtle cardiovascular or metabolic deviations prior to the onset of acute clinical symptoms [36].

Consequently, AI-driven physical activity monitoring presents an unprecedented opportunity for primary and secondary chronic disease prevention through just-in-time adaptive interventions (JITAIs) and personalized behavioral modification [33].

However, the widespread implementation of these digital health innovations is complicated by systemic socioeconomic disparities. The "digital divide" posits that the populations most vulnerable to NCDs - often marginalized, low-income, or elderly demographics - are the least likely to have access to advanced wearable technologies or the digital literacy required to utilize them effectively [47]. Furthermore, the algorithms driving these predictive models are frequently trained on homogenous datasets, leading to algorithmic biases that may misclassify or underscore risks in racially and ethnically diverse populations [29].

If deployed without a strict framework for health equity, AI-driven wearables risk exacerbating the very health disparities they have the potential to mitigate [5].

This narrative review critically examines the role of wearable devices and AI-driven physical activity monitoring in public health, establishing the background and rationale for integrating these technologies into chronic disease prevention protocols.

2. Methodology

This narrative literature review was conducted to identify and synthesize studies addressing the technical mechanisms, clinical applications, and public health implications of AI-driven wearable devices in physical activity monitoring. Electronic searches were performed in PubMed, Scopus, and Web of Science for articles published between January 2010 and January 2026.

The search strategy combined Medical Subject Headings (MeSH) and free-text terms, including: "wearable devices", "artificial intelligence", "machine learning", "deep learning", "physical activity monitoring", "chronic disease prevention", "cardiovascular disease", "diabetes", "health equity", "algorithmic bias", and "digital public health".

Boolean operators (AND, OR) were utilized to refine the search. Reference lists of relevant articles were also screened to identify additional foundational studies.

Eligible publications included randomized controlled trials, observational cohorts, algorithm validation studies, and systematic reviews examining the efficacy of wearable sensors and AI in chronic disease management and behavioral modification. Only English-language full-text articles were included. The selected literature was analyzed using a qualitative narrative synthesis focusing on three primary data domains: sensor technology and ML architectures, clinical applications in NCDs, and socioeconomic/equity implications.

3. Results

3.1 Biological and Behavioral Mechanisms of AI-Driven Wearables

The efficacy of wearable devices in chronic disease prevention is mediated through a synergistic combination of biological surveillance and behavioral modulation [21]. Biologically, wearables transcend the limitations of episodic clinical assessments by continuously harvesting high-resolution, longitudinal time-series data in free-living environments. This continuous data stream enables the establishment of a robust, highly individualized physiological baseline [51].

Artificial intelligence (AI), utilizing unsupervised anomaly detection algorithms, continuously evaluates incoming multi-sensor data against this normative baseline. Subclinical deviations - such as a progressive decline in heart rate variability (HRV) or sustained elevations in resting heart rate (RHR) - function as digital biomarkers, signaling autonomic nervous system dysregulation, systemic inflammation, or impending metabolic decompensation long before the manifestation of acute symptoms [32].

Behaviorally, AI-driven interventions leverage principles of operant conditioning to facilitate sustained lifestyle modifications[1]. Machine learning models synthesize contextual variables (e.g., location, time of day, current physical activity status) to deploy Just-In-Time Adaptive Interventions (JITAIs) [31]. These personalized, context-aware nudges - delivered via haptic feedback or visual prompts - disrupt prolonged sedentary periods and encourage goal-oriented physical activity, thereby directly addressing the behavioral risk factors associated with non-communicable diseases [23].

3.2 Types of Wearable Biosensors and AI Architectures

The translation of raw biological signals into actionable epidemiological data requires the integration of sophisticated microelectromechanical systems (MEMS) with advanced computational architectures [13].

The primary sensor modalities and their corresponding AI frameworks are detailed below and summarized in Table 1.

3.2.1 Inertial Measurement Units (IMUs)

Using triaxial accelerometers and gyroscopes, IMUs capture spatial orientation, angular velocity, and linear acceleration [4]. Deep learning architectures, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, automatically extract spatio-temporal features from raw IMU data. This enables highly accurate Human Activity Recognition (HAR), distinguishing between complex ambulatory modalities (e.g., ascending stairs vs. cycling) with accuracies frequently exceeding 92% [36].

3.2.2 Photoplethysmography (PPG)

Utilizing optical sensors to detect volumetric changes in the microvascular bed, PPG provides continuous monitoring of hemodynamics [32]. Advanced signal processing and CNNs filter motion artifacts to derive precise measurements of heart rate, HRV, and peripheral oxygen saturation (SpO2).

3.2.3 Single-lead Electrocardiography (ECG)

Modern smartwatches frequently incorporate dry electrodes to record cardiac electrical activity. Deep CNNs, trained on vast clinical repositories, analyze these waveforms to identify arrhythmias with diagnostic precision approaching that of clinical-grade Holter monitors [32].

Table 1. Comparative characteristics of wearable sensors and AI architectures in physical activity monitoring

Sensor Modality	*Primary Physiological Data*	*Typical AI/ML Architecture*	*Clinical Applications*	*Main Limitations*
Inertial Measurement Units (IMUs)	*Kinematics, spatial orientation, step count*	*CNNs, RNNs, Random Forests*	*Human Activity Recognition, fall detection, gait analysis*	*Cannot capture internal metabolic load; susceptible to movement artifact*
Photoplethysmography (PPG)	*Blood volume changes, HR, HRV, SpO2*	*CNNs, Autoencoders, Signal Processing*	*Arrhythmia detection, sleep staging, stress monitoring*	*Signal degradation by motion, ambient light, and high melanin content*
Single-lead ECG	*Cardiac electrical activity*	*Deep CNNs*	*Atrial fibrillation detection, bradycardia/tachycardia alerts*	*Requires active user initiation (in most consumer devices); limited to single-lead morphology*
Continuous Glucose Monitors (CGM)	*Interstitial glucose fluid concentration*	*LSTMs, Gradient Boosting*	*Diabetes management, postprandial glucose prediction*	*Minimally invasive, requires frequent replacement, high cost*

Overview of the primary wearable sensor modalities, their corresponding artificial intelligence architectures, clinical applications, and principal technical limitations.

3.3 Clinical Applications in Chronic Disease Prevention

The integration of these technologies has yielded substantial clinical benefits across multiple chronic disease paradigms, as illustrated in the outcome data summarized in Table 2 and Table 3.

Table 2. AI-Driven Wearable Data Pipeline for Chronic Disease Prevention

Pipeline Layer	Stage Name	Description	Key Components & Technologies
Layer 1	**Data Acquisition**	Continuous, multimodal collection of raw physiological and kinetic data in free-living environments.	IMUs, PPG sensors, Single-lead ECG, CGMs
Layer 2	**Pre-Processing**	Cleaning and standardizing raw sensor data to ensure quality and reliability for algorithmic analysis.	Artifact removal, signal filtering, data normalization
Layer 3	**AI/ML Inference**	Execution of deep learning models for pattern recognition, physiological baseline establishment, and event prediction.	CNNs, RNNs, Human Activity Recognition (HAR), anomaly detection, predictive forecasting
Layer 4	**Clinical Output**	Translation of algorithmic inference into actionable, real-time interventions and longitudinal clinical tracking.	Just-In-Time Adaptive Interventions (JITAIs) for users, aggregated digital biomarkers via Electronic Health Record (EHR) integration for clinicians

Sequential stages of data processing, from raw sensor acquisition to actionable clinical outputs and behavioral interventions.

3.3.1 Cardiovascular Diseases (CVD)

The deployment of wearable PPG and ECG for population-level cardiovascular surveillance has been validated by massive prospective cohorts, such as the Apple Heart Study (n > 400,000) [32]. AI algorithms successfully identified pulse irregularities suggestive of atrial fibrillation, enabling opportunistic screening of asymptomatic individuals.

Furthermore, continuous monitoring of the external physical load (actigraphy) relative to the internal physiological response (HRV) has proven highly effective in cardiac rehabilitation, allowing for the early detection of cardiovascular decompensation [41].

3.3.2 Metabolic Disorders and Type 2 Diabetes (T2DM)

The synthesis of CGM data with wearable actigraphy represents a breakthrough in metabolic health [19]. Recurrent neural networks synthesize glucose metrics with real-time physical activity data to forecast glycemic excursions 30 to 60 minutes in advance.

This predictive capability allows for immediate behavioral corrections - such as initiating moderate physical activity to blunt a predicted postprandial glucose spike - resulting in significantly improved time-in-range (TIR) and reduced long-term HbA1c levels [19].

3.3.3 Musculoskeletal Rehabilitation

High-frequency kinematic data obtained from IMUs enables continuous, free-living analysis. In the management of osteoarthritis, AI-driven applications monitor mechanical joint loading, ensuring patients adhere to prescribed activity thresholds, thereby reducing pain and delaying further structural degeneration [41].

Table 3. Indication-specific clinical evidence and equity implications for AI wearables

Indication	Main Wearable Modality	Reported Benefit	Main Limitations & Equity Concerns	Overall Evidence Signal
Atrial Fibrillation / CVD [32]	PPG, Single-lead ECG	Opportunistic screening of asymptomatic arrhythmias	High false positive rates in active adults; sensor bias due to skin pigmentation	Strongly Favorable for screening
Type 2 Diabetes [19]	CGM + IMU	Improved glycemic control through predictive biofeedback	Devices are highly cost-prohibitive; requires high digital health literacy	Highly promising
Osteoarthritis / Rehab [41]	IMU arrays	Continuous gait analysis, adherence to joint loading limits	Algorithms often trained on healthy gaits, misclassifying pathological movement	Moderately favorable
General Physical Inactivity [1]	IMU + PPG	Increased MVPA through Just-In-Time Adaptive Interventions	"Digital Divide" - those needing intervention most are least likely to own devices	Favorable, but highly unequal access

Summary of the reported clinical benefits, limitations, equity concerns, and overall evidence signals for AI-driven wearable applications across major chronic conditions.

3.4 Implications for Health Equity and Algorithmic Fairness

While the clinical efficacy of AI-driven wearables is well-documented, their widespread deployment has illuminated profound vulnerabilities regarding global health equity [24].

The data reveal three primary mechanisms by which these technologies currently exacerbate the "digital divide" [5];[47].

3.4.1 Socioeconomic Access Barriers

High-fidelity smartwatches and continuous monitoring systems remain cost-prohibitive for large segments of the global population. Consequently, adoption is heavily skewed toward younger, affluent, and digitally literate demographics, systematically excluding the marginalized and aging populations who statistically bear the highest burden of chronic disease [47].

3.4.2 Algorithmic Bias

Machine learning models are fundamentally constrained by the demographic diversity of their training data [29]. Models trained predominantly on healthy, Caucasian cohorts frequently demonstrate degraded accuracy when applied to individuals with mobility impairments, older adults, or people of color [33].

3.4.3 Sensor Physics and Skin Pigmentation

A critical hardware limitation exists within optical PPG sensors, which utilize green light to measure blood volume. Because melanin absorbs light at these specific wavelengths, individuals with darker skin tones frequently experience significantly higher rates of signal degradation and inaccurate heart rate estimations compared to individuals with lighter skin tones [5].

4. Discussion

The evidence synthesized in this narrative review indicates that AI-driven wearable devices constitute a biologically plausible and clinically promising group of digital interventions in public health. However, their therapeutic and preventative value is heavily context-dependent and socioeconomically stratified [10];[36].

The preventative rationale for wearables derives from their capacity to continuously monitor multimodal physiological data and deliver personalized behavioral feedback, thereby addressing the root modifiable risk factors of chronic diseases [4]; [44].

This mechanistic potential translates into clinically meaningful public health benefits only when algorithmic models are accurate across diverse populations and when access barriers are mitigated [5]; [47]. The most convincing signal of efficacy is observed in cardiovascular screening and metabolic disease management, where the integration of PPG, ECG, and CGMs with deep learning architectures has demonstrated robust predictive capabilities [19]; [32].

Despite these advantages, the principal limitation of the AI wearable literature lies in the marked heterogeneity of the devices being studied, the lack of open-source algorithm transparency, and the insufficient representation of diverse populations in clinical trials [5]; [33]. Commercial algorithms act as protected intellectual property, preventing independent scientific validation [41]. Furthermore, a substantial portion of the clinical trials suffer from profound selection bias, predominantly enrolling highly motivated, digitally literate individuals [47]. Consequently, outcomes often cannot be meaningfully extrapolated to the marginalized populations bearing the highest burden of chronic disease [24].

Furthermore, structural barriers are compounded by algorithmic bias. Machine learning models inherently reflect the data upon which they are trained [29].

A highly documented example is the racial bias inherent in optical PPG sensors; melanin absorbs the specific wavelengths of light used by many green-light PPGs, resulting in less accurate heart rate and SpO2 readings in individuals with darker skin tones [5]; [8].

If clinical decisions are increasingly based on AI wearable outputs, these uncorrected biases will operationalize structural discrimination within digital public health [29].

5. Conclusions

Wearable devices integrated with artificial intelligence represent a biologically credible and clinically promising class of digital interventions in public health. By facilitating the capture of continuous, high-fidelity physiological data and delivering automated, personalized behavioral interventions, these devices effectively target the modifiable risk factors underlying non-communicable diseases. The clinical value of these technologies is particularly substantial in cardiovascular screening, metabolic monitoring, and real-time physical activity promotion.

However, a severe discrepancy exists between the diagnostic promise of these technologies and their population-level implementation. Algorithmic bias, variable sensor accuracy across diverse skin phenotypes, and the prohibitive cost of commercial devices continue to limit generalizability and threaten to widen the digital health divide.

Future progress necessitates rigorous regulatory oversight, open-source algorithm validation, and the strict implementation of inclusive design principles. A more socially conscious and equitable deployment of digital health products is required for AI-driven physical activity monitoring to fulfill its transformative potential in global chronic disease prevention.

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