Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X Volume 3, Issue 11, 2025

SMART WEARABLE SYSTEMS DEVICES FOR PHYSICAL FITNESS

Hussain Mehdi[*1], **Syed Khaldoon Khurshid**[2], **Talha Waheed**[3], **Waqas Haider**[4], **Maryam Khan**[5]

[1,2,3,4,5]*Department of Computer Science, University of Engineering and Technology Lahore, Pakistan*

[*1]hussainmehdi637@gmail.com,[2]khaldoon@uet.edu.pk, [3]twaheed@uet.edu. pk, [4]waqasbutt@uet.edu.pk, [5]2025smscs02@uet.edu.pk

DOI: https://doi.org/10.5281/zenodo.17548597

Keywords
Wearable systems, health monitoring, body composition, muscular strength, fitness tracking, biosensors and smart watches

Article History
Received: 15 September 2025
Accepted: 25 October 2025
Published: 07 November 2025

Corresponding Author: *
Hussain Mehdi

Abstract
In this paper, we describe wearable technology. Wearable technology has revolutionized health and fitness monitoring by providing real-time tracking of physiological parameters. This paper reviews various wearable systems, including smart watches (SM), fitness trackers, smart clothing and biosensors, highlighting their applications in health monitoring, physical activity tracking, chronic disease management, and rehabilitation. It discusses the technological advancements, challenges, and future prospects of wearable health and fitness systems. Smart devices, such as smart watches and fitness bands, are widely used to monitor cardiovascular endurance, muscular strength, muscular endurance, flexibility, and body composition, leveraging sensors for heart rate, motion, and bio impedance, alongside AI-driven insights. These devices offer accessible fitness tracking but face significant limitations that hinder inclusivity across diverse populations. Despite their popularity, technical limitations undermine their inclusivity for diverse populations. Optical heart rate and bio impedance sensors falter with darker skin tones, tattoos, or hormonal fluctuations, yielding inaccurate data for older adults (56+), females, and non-binary/transgender users on hormone therapy. Motion sensors misinterpret movements for disabled users with tremors or limb differences, skewing strength and endurance metrics. The review also explores issues related to data accuracy, privacy, and user acceptance.

INTRODUCTION

Wearable technology is any kind of electronic device designed to be worn on the user's body. Such devices can take many different forms, including jewelry, accessories, Medical devices, and clothing or elements of clothing. The term wearable computing implies processing or communications capabilities, but in reality, the sophistication among wearable systems can vary. Devices like SM, fitness trackers, smart textiles and biosensors provide users with ongoing health insights encouraging a cautious approach to healthcare and customized fitness management. The integration of artificial intelligence (AI) and wireless connectivity has broadened the applications of wearable systems moving beyond basic fitness tracking to include chronic disease management rehabilitation and remote patient monitoring. This rapid development has spurred market growth with rising adoption among consumers, healthcare professionals and researchers [1].

This study will attempt to answer the aforementioned questions by carefully analyzing a number of wearable technology items now available on the market as well as scientific advancements in the field. In recent years, numerous assessments of the most cutting- edge wearable technologies utilized in diverse health domains have been carried out. In contrast, a large number of them have focused on a single wearable use case, such monitoring heart activity, physical activity, or the course of particular diseases. Furthermore, even though other reviews have been done with an emphasis on healthcare-marketed devices, the authors have not discovered any in the literature that compares the development of commercial wearable devices with those that are being investigated. This is on top of looking at every facet of the devices, such as the technology they employ and the problems they find, among other things. This scoping review aims to fill this gap by comparing the trend of commercial devices with published work.

1.1 Evolution of Wearable Health Systems

The development of wearable health devices can be traced back to the early 20th century when physicians began using portable medical devices for monitoring heart rate and blood pressure. However the advent of digital technology in the late 20th century marked a significant shift leading to the miniaturization of sensors and the emergence of commercial fitness trackers in the early 2000s [2] . Today, with the increase in the elderly population, the medical industry has changed dramatically, with a focus on the development of biosensors that enable real-time health monitoring, prevention and personalized medicine for a variety of chronic and acute diseases .Point-of-care technology (POCT) offers quick and patient-centered diagnostics, particularly for people with limited access to healthcare. In contrast, traditional disease diagnostic tests, which are frequently employed in hospitals and labs, are expensive, time-consuming, and require highly skilled staff. The average compound annual growth rate (CAGR) for wearable sensors worldwide is projected to be around 38% between 2017 and 2025 as healthcare regimes move more toward personalized medicine. Of these, the development of SM is anticipated to grow at a particularly rapid rate [3].

Companies such as "Fit bit Garmin" and Apple pioneered the consumer market introducing devices that track physical activity heart rate and sleep patterns. Today, wearable systems integrate multiple biosensors, AI-driven analytics and cloud-based health platforms enabling real-time monitoring and early disease detection [4]. A timeline showing key milestones in wearable health devices from early medical monitors to modern SM in figure 1.

1.2 Market Growth and Adoption

The global market for wearable healthcare devices has experienced exponential growth. According to Fortune Business Insights (2023), the wearable healthcare market is projected to exceed $200 billion by 2030 [5], driven by factors such as:

- Increased health awareness
- Rise in chronic diseases (diabetes, cardiovascular conditions)
- Advancements in AI-driven health monitoring

The COVID-19 pandemic further accelerated the adoption of wearable devices, with researchers and healthcare providers leveraging these devices for remote health monitoring and early detection of respiratory illnesses [6]. Figure 2 presents the global market trends for wearable healthcare from 2015 to 2030.

1.3 Key Components and Functionality

Wearable systems are widely used across various domains, including:

- Personal Fitness and Activity Tracking: Devices such as SM and fitness bands help users monitor physical activity, calorie expenditure, and sleep patterns, promoting a healthier lifestyle [7].
- Chronic Disease Management: Continuous glucose monitoring (CGM) systems assist diabetics in tracking blood sugar levels, while wearable ECG patches help patients with cardiovascular diseases.
- Remote Patient Monitoring (RPM): Wearable facilitate remote healthcare by transmitting real-time patient data to healthcare providers, reducing hospital visits and improving patient outcomes [8].
- Sports Performance Optimization: Athletes use wearable devices to analyze biomechanics, track hydration, and optimize training regimens for enhanced performance and injury prevention [9].

Table 1.Key Components of wearable device

Component	Function	Example Device
Biosensors	Measure heart rate, spo2, glucose levels	SM, CGMs
Accelerometer s & Gyroscopes	Track movement, activity levels, falls	Fit bit , Apple watch
ECG Sensors	Detect heart irregularities	Samsung galaxy watch, Wi things Scan watch
Wireless Modules	Enable cloud connectivity and remote tracking	Bluetooth, Wi-Fi ,5G- enable devices
AI Algorithms	Process health data for personalized insights	AI- based fitness coaching apps

1.4 Objectives of the Review

This paper provides a comprehensive review of wearable systems for health and fitness, with a focus on:

1. Examining the different types of wearable health technologies and their functionalities.
2. Evaluating the applications of wearable systems in health monitoring, fitness tracking, and rehabilitation.
3. Analyzing challenges such as data accuracy, privacy concerns, and user adoption.
4. Highlighting future research directions and technological advancements in wearable health systems.

By exploring these aspects, this review aims to contribute to the growing body of knowledge in wearable healthcare and offer insights for researchers, developers, and healthcare professionals.

2. RELATED WORK

Wearable health systems have undergone significant advancements, leading to the development of innovative devices and technologies that increase health monitoring and patient care. Wearable biosensors are attracting a lot of interest due to their potential to provide continuous, real-time physiological information in a range of healthcare-related applications through dynamic, non-invasive measurements of chemical markers in bio fluids like sweat, tears, saliva, and interstitial fluid (ISF) [12, 13] to biomedical monitoring systems, which enable continuous measurement of critical biomarkers for medical diagnostics, physiological health monitoring and evaluation [2].

Furthermore a fully integrated wearable micro needle system for continuous monitoring of ISF biomarkers has been made which measure real-time monitoring of glucose, lactate, and alcohol levels in ISF. The device, paired with a smartphone app for data capture and visualization, includes reusable electronics and a disposable micro needle array. This system has design with integrated sensors, electronics, firmware, and a mobile application. Electrochemical data was captured using an analogue front end (AFE) and transmitted via Bluetooth low-energy (BLE). On-body testing with human subjects validated the sensor data against standard reference methods (blood or breath analysis) [14].

Similarly study introduces a flexible integrated sensing array (FISA) for simultaneous and careful measurement of sweat metabolites and electrolytes, along with skin temperature, during physical activities1. The approach involves use of sensors are fabricated on a flexible PET (flexible polyethylene terephthalate) substrate and integrated with commercially available circuits on a flexible printed circuit board (FPCB) for signal processing and wireless data transmission. Electrochemical sensors measure glucose and lactate using oxidase-based aerometric detection, while Na+ and K+ levels are supervised with ion-selective electrodes (ISEs). Signal conditioning and processing are handled by analogue circuits and a microcontroller, which also enables Bluetooth-based data transmission. On-body testing involves monitoring sweat biomarkers during physical activities, with accuracy validated by comparing sensor readings to external measurements [15].

Another sweat analysis skin-interfaced wearable microfluidic device and smartphone image processing platform for analyzing regional sweating rate and sweat chloride concentration is introduced by Baker. An orange dye quantifies sweat volume, while a separate reaction detects chloride levels. A smartphone app consider images of the patch, detecting boundaries, micro channels, and reference colors to figure out sweat volume and chloride concentration. The system was tested on 312 athletes in different conditions, with results compared to conventional sweat analysis methods. Algorithms were mature to estimate whole- body sweating rate and chloride concentration from regional sweat data [16]. Wearable technology in healthcare refers to devices that patients attach to their bodies to collect health and fitness data, which they may provide to doctors, health providers, insurers and other relevant parties. Examples include fitness trackers, blood pressure monitors and biosensors. Because of these benefits, wearable medical devices — like fitness trackers, SM, electrocardiogram (ECG) monitors, blood pressure monitors and biosensors — have witnessed booming demand. The smart wearable health devices market was valued at $13.8 billion in 2020, and market is projected to exceed $200 billion by 2030 [5].

Health Monitoring Features	Measures heart rate, blood oxygen (SpO_2), ECG, stress levels, sleep patterns	Limited to pedometer, GPS- based tracking, and third-party app integration
Convenience & Usability	Always worn, enabling passive tracking and real- time alerts	Needs to be carried and manually accessed for fitness tracking
App & Ecosystem Integration	Syncs with Apple Health, Google Fit, Fit bit, and other fitness platforms	Provides a larger screen for better visualization of fitness data
Cost & Accessibility	Higher cost but offers dedicated fitness tracking	More affordable and widely available with basic fitness tracking apps

Table 2.Feature of Smart watches and Mobile Phones

2.1 Physical Activity and Fitness Tracking with Smart Devices

The way people track and manage their fitness and physical activity has been completely transformed by the introduction of SM and other mobile devices into daily life. By providing real- time data on a range of health metrics, these technologies empower users to make well-informed decisions regarding their wellness practices. This review of the literature looks at the advantages, disadvantages, and efficacy of tracking fitness and physical activity with SM and smartphone apps [10]. Advances in the device and smartphone technology, such as activity trackers and physical activity smartphone applications, have led to an exciting opportunity for delivering physical activity interventions [11]. SM and mobile phones are extensively used for monitoring bodily pastime and health. While each gadgets provide capabilities like step counting, exercise monitoring and physiological monitoring, they fluctuate in phrases of convenience, accuracy, battery life, and integration with health ecosystems. This assessment examines the strengths and boundaries of SM and mobile phones in bodily pastime and health monitoring.

Feature	Smart watches	Mobile Phones
Portability & wear ability	Worn on the wrist, providing hands- free tracking throughout the day	Carried in pockets or bags, requiring manual handling for tracking
Step Counting Accuracy	More accurate due to consistent wrist placement	Less accurate as phone placement (pocket, bag) affects motion detection
Heart Rate Monitoring	Continuous heart rate tracking with optical sensors	No built-in heart rate monitoring (unless paired with an external sensor)
Workout Tracking	Offers real-time tracking with specialized modes for different activities (e.g., running, cycling, swimming)	Requires manual input or third- party apps for detailed workout tracking
GPS Tracking	Some SM have built-in GPS for outdoor workouts	Mobile phones have more accurate GPS due to better signal reception
Battery Life	Shorter battery life (1-2 days with continuous tracking)	Longer battery life but drains faster when using fitness tracking apps

2.2 Wearable systems for patient

Wearable systems for patients' remote monitoring consist of three main building blocks:

The sensing and data collection hardware to collect physiological and movement data.

The communication hardware and software to relay data to a remote center.

The data analysis techniques to extract clinically-relevant information from physiological and movement data.

New advancement in sensor technology, microelectronics, telecommunication, and data analysis techniques have implement the development and deployment of wearable systems for patients' remote monitoring [17, 18].

2.3 Electrochemical Sensors

Roll-to-Roll Gravure Printed Electrochemical Sensors for Wearable study are to present R2R gravure printed electrodes that can be functionalized into sensors for diverse electrochemical sensing applications. The methodology involved R2R Gravure Printing, Ink formulation, electrode design, material Selection, electrode pretreatment, sensor Functionalization, electrochemical characterization, bio fluid Testing, In-situ Testing [19].

In sports domain a miniature wearable device designed for monitoring movement and biometric data during sports activities, particularly on the wrist. The device combine sensors to track skin temperature, pulse rate, and arm movements, with an inertial measurement unit for gesture detection. Basic signal processing appears on the device, while complex analysis is performed via a cloud-based application. A lightweight LiPo battery provides approximately 6 hours of operation [20].

A spatiotemporal gait analysis algorithm with a wearable inertial measurement system (IMS) to evaluate clinical markers in patients with Parkinson's disease (PD) and stroke. The system subsists of a microcontroller, triaxial accelerometer, gyroscope, and wireless transmission module. The methodology involved 24 participants (4 strokes, 5 PD, 15 healthy controls) who walked 10 meters with the IMS module attached to their feet. The accelerometer and gyroscope measured walking movements at a 100 Hz sampling rate. The spatiotemporal gait analysis algorithm processed inertial signals, detected gait phases, and estimated ankle range of motion [21].

2.4 The accuracy of Smart Watches for Vital Sign Monitoring with other devices

The study aimed to assess the long-term real-world performance of the LG G Watch R's optical heart rate sensor and examine its potential to track sleep. The accuracy of smart watch-measured heart rate was compared with readings from a CMS-60D pulse ox meter and a 3-lead ECG system (Power Lab & AD Instruments) during four volunteers taking part in 10-minute tests. All the devices were worn simultaneously, and the gathered data were synchronized and resampled. Accuracy was examined using Root Mean Square Error (RMSE), Standard Error (SE), and correlation coefficients. The research also explored the smart watch's capability for sleep monitoring by recording heart rate and accelerometer data over 4–6 hours of sleep, together with a RESMED S+ non-contact sleep monitor, which gave reference data on movement and breathing. The results were intended to establish how suitable the smart watch was for home-based dependability applications such as tracking sleep [22].

Another study by Hahnen sought to compare the accuracy and precision of these vital signs: heart rate (HR), systolic blood pressure (SBP), diastolic blood pressure (DBP), and oxygen saturation (SpO_2) with measurements from two new devices: the Body Metrics Performance Monitor and Ever last TR10 smart watch. With a protocol borrowed from ANSI/AAMI/ISO 2013 standards, 85 adult subjects from Thomas Jefferson University Hospital were tested, and data were gathered after the exclusion of

42 individuals because of calibration problems or unreliable measurements. SBP, SpO_2, and HR were measured by the Body Metrics device, whereas SBP, DBP, and HR were measured by the Ever last TR10. Both were cross-checked with a validated Cardio cap/5 hospital-grade monitor. Subjects rested before alternating measurement with investigational and control devices, yielding multiple paired comparisons across each subject. Analysis of data included calculation of mean absolute differences, percent differences, and RMSE for every vital sign, with accuracy checked versus defined clinical thresholds. Bland- Altman plots, scatterplots, and correlation analyses were employed to visually interpret results, including the capacity of the devices to signal abnormal vital signs [23].

Another study by Walzel was to determine the accuracy of SpO_2 readings on three best-selling smart watches, Apple Watch 8, Samsung Galaxy Watch 5, and Withings Scan Watch, compared with a clinically validated pulse oxy meter (Radical-7), in accordance with ISO 80601-2-61 standards. As a prospective, interventional, randomized crossover study, it enrolled 18 healthy Caucasian volunteers aged 21–26. All subjects underwent three tests, using a different smart watch on each occasion, with controlled hypoxia by non-rebreathing circuit and inhaling progressively lower oxygen concentrations. SpO_2 values were manually logged from the smart watches and the reference device at specified times, collecting 16 paired readings per test. Analysis of data used linear regression, Pearson correlation, paired t-tests, and Bland–Altman analysis to measure agreement, bias, and limits of agreement. Root-mean-square deviation (Arms) was also computed, as well as sensitivity, specificity, and diagnostic accuracy for hypoxemia detection ($SpO_2 < 90\%$), and results were further compared across varying SpO_2 ranges [24].

2.5 Smart Bands for Vital Sign Monitoring

This study by mitro describes the design, architecture, implementation, and validation of a low-cost, machine-learning- capable smart wristband for real-time physiological measurement and stress identification during emergency evacuations from large passenger ships. The system, designed around a bespoke PCB and PPG-based sensor (MAX30101), employs an nRF52840 SoC for computation and communication. It estimates pulse rate and SpO2 using signal processing algorithms and compares them to commercial devices. Stress detection is based on a unit modal PPG-based machine learning model, employing ultra-short pulse rate variability features and a linear SVM classifier, which was trained on the WESAD dataset. The model was optimized and deployed to execute on the wristband's microcontroller. External validation on 15 subjects under cognitive stressors resulted in 76% accuracy and 70% F1-score in real-time stress detection [25].

The research by Mahapatra suggests and deploys an IoT-based approach to track people automatically, trace contacts, and fence geographies for COVID-19 risk management in organizations. The approach includes an RFID and GPS-enabled wristband coupled with fingerprint authentication for the verification of users. It gathers and sends user identity, location, and health status information to a cloud database, providing real-time monitoring. A geo fencing algorithm flags unauthorized crossing of assigned boundaries, and automated contact tracing records both real-time and checkpoint location history. Data visualization and analysis are facilitated through a web portal, with automatic health status updates and alert emails. It combines hardware, cloud service, and a secure web interface to advance safety and prevention efforts [26].

The study by Khemtonglang aims at the design and creation of a smart wristband combined with an IoT-based alarm system, referred to as Drunk Mate, for real-time, noninvasive sweat alcohol monitoring. The proposed device employs a MOX gas sensor (MICS5524) to measure ethanol in sweat and sends data through an ESP32 microcontroller to the Drunk Mate platform, which shows alcohol concentrations and provides warnings according to legal BAC limits. The wristband also included a 3D-printed casing, a sweat collection area, and utilized a rechargeable battery system. Artificial sweat preparation, sensor calibration, specificity, and accuracy validation, and simulated real-time alcohol monitoring were undertaken in the research. Results indicated the system's ability to identify alcohol concentration in sweat and alert on time effectively, validating its feasibility for personal and legal security purposes [27].

3. Limitations

General wearable biosensors encounter a number of issues, with challenges at the body-sensor interface, as a few examples, being surface bio fouling and inefficient sample transport across the sensor. Furthermore, many bio receptors present stability issues, while the multiplicity of steps for example or the challenges of performing receptor regeneration with multi-step bio affinity assays further complicates this. Not to mention, accurate calibration for on-body samples is a hurdle when performing on- body testing. Wearable biosensors still face several key obstacles which include limited battery technology which reduces the autonomy of the device and restricts the power needed for sensing, data processing, and wireless communication. Also, barriers including cultural attitudes, such as worry over the stigma of using medical devices at home, as well as concerns around data security and privacy have inhibiting the widespread adoption of wearable biosensors. Current, continuous glucose monitors (CGMs) rely on invasive needle-based sensors and have limited applicability as they are only able to detect a single analytic. Micro needle sensors show promise as an alternative; however, most studies have been limited to in vitro studies, with few demonstrations on-body. Even in the rare instances of on-body single analytic sensing, the devices were not integrated systems and had poor analytical performance. The transition of micro needle technology from laboratory environments to everyday wearable applications is fraught with challenges as it needs multidisciplinary efforts. Also, transdermal micro needles will have limits around drug delivery due to limitations in the drug payload.

3.1 Accuracy issues

Wearable technologies have numerous performance and accuracy issues with sports and health outcomes-related metrics. Wearing technology in swing sports adds weight that influences the arms' movement. For gait analyses, gait studies that only measure the ankle joint angles in the sagittal plane should incorporate the measurement of the knee and hip joints as well as the evaluation of movement in the coronal and horizontal planes. The inertial sensors also suffer from integration errors, which should be minimized. Wearable optical sensors for heart rate monitoring have validity issues with rate of errors due to motion artifact, and skin types and signal crossover. Although one study showed no statistically significant accuracy difference between heart rate if an individual had skin of different tones, there is considerable heart rate accuracy variability between devices and physical activity and estimates demonstrate an average measurement error 30% higher with activity than at rest. The discrepancies between devices in interpreting and responding to changes of activity also complicates decision making. Furthermore, other studies sampled limited devices making it difficult to properly attribute variability of error to sensor technology or brand. Therefore, developers of algorithms to calculate digital biomarkers need to understand measurement error and data quality to ensure useful information relayed to healthcare professionals.

Traditional methods of collecting sweat via absorbent pads and external laboratory instruments are inadequate for general use and monitoring. Reliable analysis of sweat requires that it be sufficiently isolated from skin and/or environmental contaminants. The biggest issues with microfluidic sweat patches were mechanical issues, such as sweat not advancing properly due to low rates of sweat, adhesive and/or sweat patch delamination, back flow, and insufficient colorimetric reaction. Total body sweat loss must be understood vis-a-vis localized sweat rates, which may necessitate the use of multiple patches across multiple body locations or calibration for each individual. Design improvements may include reducing adhesive areas to counteract accumulation and minimize collection error, and increasing patch collection zones to account for low rates of sweat. Lastly, many investigations do not reflect the duration of real-life activities, or low-level exercise on sweat rates. Additional investigation or the creation of algorithms is necessary for duration or varying body regions, environmental conditions, and physical activity [16].

The main obstacles for wearable and implantable diabetic interventions consist of guaranteeing biosafety and ensuring biocompatibility over the long-term. While biocompatible polymers are utilized for encapsulation of devices, the long-term stability of those polymers was not considered. Responsive insulin delivery systems are also dangerous for accidental burst release of insulin. Given that insulin can only be delivered subcutaneously, time delays can occur, in part due to the absence of direct access to portal circulation to facilitate uptake. Similarly, there is a need to optimize the membrane materials for islet encapsulation so they will block immune cells while still allowing the exchange of studied nutrients. As large animal studies have been undertaken, human trials also are needed to substantiate the safety and efficacy of the devices. In addition, personalized therapy will still need additional research in individual physiologic variation. There are some real-world considerations with wearable insulin pumps, including the need for repeated cannula replacement, and risks of kinking or bending the cannula, as well as potential infection or occlusion from foreign body reactions [13].

3.2 Smart Watches

Smart watches are useful like apple Samsung and MI for monitoring and supporting physical health, but they have limitations when addressing cardiovascular endurance, muscular strength, muscular endurance, flexibility, and body composition. Below is a concise breakdown of these limitations for each these physical health component.

3.2.1 Cardiovascular Endurance

Accuracy Issues: Optical heart rate sensors can be less accurate during high-intensity interval training (HIIT), rapid heart rate changes, or water-based activities (e.g., swimming) due to motion artifacts or poor skin contact.

Limited Metrics: VO2 max estimates are approximations and may not match lab-based tests. Metrics like lactate threshold or detailed aerobic efficiency are often absent.

Environmental Factors: Wrist-based sensors may struggle in extreme temperatures or with improper fit, affecting data reliability.

Medical Limitations: Features like ECG (e.g., Apple Watch) are not diagnostic tools and cannot replace professional cardiac assessments for conditions like arrhythmias [37].

3.2.2 Muscular Strength

Smart watches have notable limitations in tracking muscular strength accurately. One of the primary issues is their inability to detect resistance loads, such as the weight lifted during strength training. Without sensors that can measure force output or resistance, smart watches cannot provide meaningful insights into strength progression or one-rep max calculations. Additionally, these devices often struggle to recognize strength training movements—particularly those involving free weights, machines, or bodyweight exercises—leading to incomplete or inaccurate workout logs. Furthermore these are the more limitations as define below.

Inaccurate Exercise Detection: Smart watches may misidentify or fail to track specific strength exercises (e.g., deadlifts, kettle bell swings) without manual input or third-party app integration.

No Weight Tracking: Most devices cannot automatically detect weights lifted, requiring users to log resistance manually, which can be cumbersome.

Form and Technique: Smart watches cannot assess exercise form or technique, critical for safe and effective strength gains, necessitating external coaching.

Limited Gym Integration: Compatibility with gym equipment (e.g., smart barbells) is often limited or brand-specific.

3.2.3 Muscular Endurance

Rep Counting Errors: Motion sensors may inaccurately count repetitions for complex or bodyweight exercises (e.g., burpees, pull-ups), especially with inconsistent movement patterns.

Fatigue Monitoring: Smart watches lack direct measures of muscle fatigue or endurance capacity, relying on indirect metrics like heart rate or subjective user input.

Exercise Variety: Pre-set workout modes may not cover niche endurance activities (e.g., rock climbing), limiting tracking versatility [34].

3.2.4 Flexibility

No Range of Motion Tracking: Smart watches cannot measure joint mobility or flexibility improvements, offering only timed stretching/yoga sessions or heart rate data.

Limited Guidance: Built-in flexibility workouts (e.g., Fit bit, Apple Fitness+) are basic and may not suit advanced users or those needing tailored mobility plans.

Subjective Assessment: Progress in flexibility relies on user self- reporting, as devices cannot quantify improvements like a physical therapist would.

Indirect Metrics: Stress or recovery scores (e.g., Garmin's Body Battery) provide tangential insights but don't directly correlate with flexibility gains.

3.2.5 Body Composition

Smart watches such as Apple, MI and Samsung watches monitor body composition (e.g., body fat, muscle mass, BMI) using bio impedance sensors or smart scale integration, often enhanced by AI-driven insights. However, these significant limitations compromise their inclusivity for diverse populations

Bio impedance Variability: Devices with bioelectrical impedance (e.g., Samsung Galaxy Watch) are sensitive to hydration, skin temperature, and measurement timing, leading to inconsistent body fat or muscle mass readings.

Limited Scope: Most smart watches don't measure visceral fat, bone density, or other advanced body composition metrics, unlike DEXA scans or professional tools.

Scale Dependency: Accurate body composition often requires paired smart scales (e.g., Fit bit Aria), adding cost and complexity.

Non-Clinical Accuracy: Results are estimates, not medical-grade, and can mislead users without proper context or professional interpretation [31, 32].

3.2.6 Inclusivity Barriers

User Compliance: Effectiveness depends on consistent wear, correct usage, and manual data entry (e.g., food logging), which can be time-consuming or neglected.

Battery Life: Intensive tracking (e.g., GPS, heart rate) drains batteries quickly, potentially interrupting long workouts or multi- day monitoring.

Data Overload: Excessive metrics can overwhelm users, leading to misinterpretation or focus on less relevant data.
Privacy Concerns: Health data shared with apps or cloud services raises security risks if not properly managed.
Not a Substitute for Professionals: Smart watches cannot replace trainers, dietitians, or medical professionals for personalized plans or clinical diagnoses.

Age Impact:
Young Adults (18-35): Lack of detailed metrics (e.g., lactate threshold) limits support for advanced fitness goals.

Middle-Aged Adults (36-55): Generic metrics don't address muscle loss or joint health, key concerns for this group.

Older Adults (56+): Missing metrics for mobility or fall risk reduce relevance for aging-related health.

Gender Impact:

Male: Higher muscle mass requires specific strength metrics, often absent in watches.

Female: Hormonal effects on endurance or body composition are ignored, limiting metric utility [30].

3.3 Technical Limitations in Wearable Biosensor

A number of limitations and disclosures identified across the studies considered. In some instances, raw datasets and analyzable datasets were too large for public sharing, but they are available on reasonable request as is the firmware and app source code. In an on-body micro needle study, there were only nine healthy, non- randomized participants, all selected from the research group, and data collection and analysis were not blinded. In another study, murine macrophage cells were used with no authentication. An optical heart rate accuracy developed, but three participants were excluded from the analysis as they did not have complete ECG data. Further, several studies disclosed conflicts of interest including a corresponding author with equity in, and a board seat at, the author's company, and other authors were employed by organizations in developing or funded the technologies.

To condition signals effectively and provide accurate measurements, wearable biosensors need low-pass filters to limit noise and interference. For sweat patches analyzed in smartphone mode, we applied a manual approach to analyze the raw images of the patches. This effort emphasizes the need for automated image analysis software to limit analysis time and inaccuracies due to human error. Furthermore, optical reflectance measurements in smart watch mode must also address potential confounding sources of error relating to interpreting specular vs. diffuse reflection, and the changing optical signal due to motion during the measurement process.

The study by walzel on smart watch SpO2 accuracy had a sample of healthy Caucasian participants between the ages of 21-26 years. The authors admitted there would be variability in chronic elderly patients or when accounting for differences in pigmentation which can affect light transmission and reflectance. The smart watch SpO2 study participants had a gender imbalance [24].

In the wristband study that developed a custom stress detection wristband, the number of subjects was limited. In the smart watch vital signs study, participant data from 41 subjects (out of 127 who enrolled) were disregarded due to excessive variation in sequential standard measurements [23, 25].

Various methodological limitations were noted across studies with wearable health monitoring devices. One blood pressure (BP) validation with a study design varied from typical protocols in that the study used an automated monitor at the hospital in place of a mercury sphygmomanometer using auscultation and did not blind participants to the investigational device readings. A smart watch- based SpO2 study failed to create hypoxemia in participants by producing consistent levels of desaturation across participants and had few measurements below 80% SpO2. Controlled, resting conditions and verified smart watch positioning were used for the study, which probably did not reflect normal use where movement artifacts and mis positioning can reduce accuracy. In studies about oxygen saturation, invasive measures such as arterial oxygen saturation (SaO2) were intentionally not obtained due to safety considerations. Data filtering in studies included excluding values based upon percentage difference or threshold values. One sleep analysis article only reported on a 60-minute sleep, which greatly limited the analysis. For stress detection, the model that was trained used data from a different device and PPG sensor as the validation PPG sensor so that comparison is difficult. More generally, inappropriate methodological approaches across wearable-based stress studies limit appropriate comparisons because stress induction protocols are not standardized, ground truth acquisition methods are not standardized (including stress self-reports), and there is an overreliance on cross-validation approaches rather than held-out test sets.

The analysis and functioning of wearable health monitoring devices exhibited various limitations. Physiological signal readings from wearable were inaccurate compared to professional measurements, particularly during the 20 minutes prior to going to sleep and upon waking. The Body Metrics tri order, for example, produced an inaccurate systolic blood pressure reading when used at pressures deviating from calibration, which illustrates the shortcomings in the calibration mechanism. Misleading consumer-based vital sign monitors can produce a wrong impression of consumers' health and lead to errors in diagnosis or inappropriately delaying medication commencement by suggesting that it might be harmful. Smart watches are not approved for clinical use at SpO2 levels and do not guarantee that the algorithm model is disclosed. The reported times for SpO2 were also inconsistent between devices, with reading times ranging from 12-30 seconds, which were difficult to compare and exhibit the potential for time-shifting. Motion artifacts and long durations to measure also limit its clinical use. The author- constructed stress detection solution relied on binary classification (stress/no stress). The microcontroller used for real-time inference had limited processing potential, restricting the complexity of the stress detection algorithm. Specific selections for the stress detection wristband for hardware options were dependent both on physical size, and limited financial resources.

The application had many technical, secure and practical limitations. The application made use of passive RFID, which cannot determine if the user is closer or further away to each other. The application was to be used inside an organization, as such it hinders its own capabilities in return. In addition, successful deployment of the application would require the organization to individually have good internet and Wi-Fi infrastructure. In addition, while Bluetooth Low Energy (BLE) is commonly associated with contact tracing, it has limitations including low security, low bandwidth, potential loss of connection to the user, and not being suitable for transferring large amounts of data. IoT devices, and especially IoT devices in the healthcare space, are particularly susceptible to a cyber-attack due to low security regarding authorization, poor protection of web interfaces, and weak encryption protocols. Moreover, larger digital contact tracing technology has similar issues such as scalability, lack of ethics, low smartphone penetration, and lack of transparency, which lessen their credibility, as well as making them difficult to implement voluntarily due to privacy concerns or reluctance to trial the technology.

Table 3 Limitations of 2 different brands

Components	Samsung Galaxy	Xiaomi MI Band
Heart Rate Monitoring	The Galaxy utilizes a photo plethysmo graphy (PPG) sensor for heart rate monitoring. While it provides basic heart rate data, it lacks advanced features like ECG or VO_2 max estimation	The MI Band also uses a PPG sensor. Reviews indicate that while it performs adequately during steady-state activities
Muscular Strength	The Galaxy does not offer features to measure muscular strength, such as tracking weight lifted or repetitions during resistance exercises	While the MI Band includes modes like "freestyle" and "yoga," it lacks specific functionalities to assess muscular strength, such as tracking resistance levels or providing feedback on strength training exercises
Muscular Endurance	The device tracks general activities but does not provide detailed insights into muscular endurance, such as sustained muscle activity over time or fatigue levels	The MI Band tracks activities like rowing and jump rope but does not offer in-depth analysis of muscular endurance, such as time to fatigue or muscle recovery rates
Flexibility	The Galaxy does not include features to assess flexibility, such as measuring joint range of motion or providing flexibility	While the Mi Band includes a yoga mode, it primarily tracks heart rate and duration, lacking capabilities to assess improvements

	training programs	in flexibility or range of motion
Body Composition	The device does not offer features to assess body composition metrics like body fat percentage or muscle mass	The MI Band lacks sensors or algorithms to measure body composition, limiting its utility in tracking changes in fat or muscle mass over time

3.4 Smart Ring

Sensor Accuracy: Heart rate reliable for steady runs but less accurate for darker skin tones (up to 20% error) or rapid HR changes (e.g., HIIT). SpO2 measurements inconsistent.

Limited Workout Tracking: Auto-detects only walking/running; strength training (e.g., free weights) poorly tracked, no gyroscope/GPS for distance accuracy.

No Advanced Metrics: Lacks lactate threshold, muscle fatigue, or flexibility range, relying on basic data (steps, HR).

Android-Only: Incompatible with iPhones, limiting full AI features (e.g., Energy Score) to Samsung phones.

Activity Gaps: Misses long walks or non-standard exercises (e.g., Pilates), requiring manual logging.

Age: Young adults' intense workouts face HR errors; older adults' arrhythmias skew data.

Gender: Females' hormonal shifts (menstrual cycles, menopause) distort HRV; non-binary/transgender users' hormone therapy unaccounted.

Disabilities: Tremors or limb differences disrupt tracking; no adaptive exercise modes.

Cultural/Socioeconomic: Western-centric metrics (e.g., running) overlook cultural activities (e.g., dance); $399 cost excludes low-income users.

Privacy: Menstrual cycle data risks exposure, deterring females/non-binary users [35].

3.5 Smart Bands

Smart rings designed to monitor cardiovascular endurance, muscular strength, muscular endurance, flexibility, and body composition. Below are limitations, including inclusivity barriers for diverse populations (age: young adults 18-35, middle-aged adults 36-55, older adults 56+; gender: male, female, non- binary/transgender; disabilities, cultural backgrounds, socioeconomic statuses).

3.6 General Limitations

The Samsung Galaxy and Xiaomi MI Band are popular budget-friendly fitness trackers that offer a range of features for general health monitoring. However, they have limitations in accurately assessing specific components of physical fitness, such as cardiovascular endurance, muscular strength, muscular endurance, flexibility, and body composition. Below is a detailed overview of these limitations, supported by relevant references:**While the Samsung Galaxy and** Xiaomi Mi are effective for basic activity tracking and general health monitoring, they have significant limitations in assessing specific components of physical fitness. For comprehensive evaluation of cardiovascular endurance, muscular strength and endurance, flexibility, and body composition, more advanced devices or professional assessments are recommended [28 , 29].

3.6.1 Sensor Accuracy and Physiological Variability

Smart devices monitor cardiovascular endurance, muscular strength, muscular endurance, flexibility, and body composition, but face limitations that hinder inclusivity for diverse populations across age (young adults: 18-35, middle-aged adults: 36-55, older adults: 56+), disability, gender (male, female, non-binary/transgender), and AI integration. Below are the key limitations and their inclusivity impacts.

3.6.2 Usability and Accessibility Challenges

Optical heart rate sensors, accelerometers, and bio impedance are less accurate for darker skin tones (up to 20% heart rate error), tattoos, hairier wrists, or hydration shifts, affecting metrics like heart rate (cardiovascular endurance), rep counting (strength/endurance), and body fat (composition).

3.6.3 Lack of Personalization

Small screens, complex apps, and manual inputs (e.g., logging weights) hinder use, especially for less tech-savvy or physically limited users.

3.6.4 Cost and Economic Barriers

Generic workouts and insights fail to address individual fitness needs, reducing effectiveness for diverse users. Young adults' niche goals (e.g. Cross Fit) and older adults' mobility needs (e.g., fall prevention) are underserved. Adaptive exercise plans for wheelchair users or chronic pain are absent.

3.6.5 Privacy and AI Data Risks

Devices ($50-$600) and subscriptions (e.g., Fit bit Premium
$9.99/month) are costly; short battery life disrupts use. Older adults on fixed incomes and young adults with budget constraints face affordability issues. Additional costs for accessible accessories (e.g., larger straps) burden disabled users.

3.6.6 Privacy and AI Data Risks

Sensitive health data (e.g., heart rate, menstrual cycles) shared with apps raises security risks, especially with AI processing. Older adults with lower privacy awareness are vulnerable to breaches. Females and non-binary/transgender users sharing cycle/hormone data face higher risks.

3.6.2 Limited AI Use in Smart Devices

The limited use of AI in smart devices typically refers to employing artificial intelligence for specific, narrowly defined tasks to enhance functionality while balancing constraints like power consumption, privacy, cost, and hardware limitations. Below things are used in a limited capacity in smart devices [36].

- Voice Assistants
- AI Body Recognition

4. FUTURE WORK

1. **Enhanced Sensor Technology**: Develop adaptive optical and bio impedance sensors to account for darker skin tones, tattoos, hormonal fluctuations, and atypical body types, improving accuracy for older adults, females, non-binary/transgender users, and disabled individuals with limb differences.
2. **Accessible Interfaces**: Design larger, high-contrast displays, voice/haptic controls, and multilingual apps to support older adults with low tech literacy, disabled users with visual/motor impairments, and non-English- speaking populations.
3. **Specialized Metrics for Older Adults (56+):** Embed sensors for mobility and balance (e.g., gait analysis, fall risk scores), integrating AI to predict and prevent age- related declines. Create simplified dashboards highlighting mobility metrics, accessible for older adults with varying tech literacy
4. **Personalized AI Models**: Train AI with diverse datasets reflecting age, gender, disability, and cultural fitness practices (e.g., Tai Chi), enabling tailored plans for young adults' niche goals, older adults' mobility
needs, females' cycle-aware training, and adaptive exercises for wheelchair users.
5. **Affordable Solutions**: Reduce device costs (currently
$50-$600) and eliminate subscription fees (e.g., $9.99/month) through open-source AI or subsidized models, ensuring access for low-income and disabled users.
6. **Robust Privacy Frameworks**: Implement end-to-end encryption and anonym zed AI processing to protect sensitive data (e.g., menstrual cycles, hormone therapy), building trust among gender-diverse and disabled users.
7. **Advanced AI Integration**: Expand AI capabilities beyond voice assistants and body recognition to include real-time motion correction, adaptive workout adjustments, and predictive health analytics, optimized for low-power hardware to enhance functionality for all users

5. CONCLUSION

Smart devices for physical fitness monitoring are limited by inaccurate sensors, inaccessible interfaces, generic AI-driven plans, high costs, privacy risks, and constrained AI use, disproportionately impacting older adults, disabled users, females, non-binary/transgender individuals, and low-income or culturally diverse populations. These barriers hinder equitable access to reliable fitness tracking. Future advancements in adaptive sensors, inclusive AI, accessible designs, affordability, and secure data handling can bridge these gaps, ensuring smart devices serve diverse needs effectively. Until then, combining device use with professional guidance remains essential for inclusive and accurate physical fitness monitoring.

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