

# **Advancements in Wearable Sensor Technologies for Health Monitoring: A Systematic Review of Clinical Applications, Rehabilitation, and Disease Risk Assessment**

Bonsang Gu, Hyeon Su Kim, HyunBin Kim, Jun-Il Yoo

Submitted to: JMIR mHealth and uHealth  
on: April 17, 2025

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# Advancements in Wearable Sensor Technologies for Health Monitoring: A Systematic Review of Clinical Applications, Rehabilitation, and Disease Risk Assessment

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## Abstract

**Background:** Wearable sensor technologies, such as inertial measurement units (IMUs), smartwatches, and multi-sensor systems, have emerged as valuable tools in clinical and real-world health monitoring. These devices allow continuous, non-invasive tracking of gait, mobility, and functional health across a variety of populations. However, significant challenges remain, including variability in sensor placement, data processing methodologies, and insufficient validation in real-world settings.

**Objective:** This systematic review aims to evaluate recent literature on the clinical and research applications of wearable sensors. Specifically, it investigates how these technologies are used to assess mobility, predict disease risk, and support rehabilitation. It also identifies limitations and proposes future research directions.

**Methods:** The review was conducted according to PRISMA guidelines. A comprehensive search of PubMed, Scopus, and Web of Science databases was performed for studies published in the past ten years. Inclusion criteria focused on studies using wearable sensors in clinical or real-world environments. A total of 30 eligible studies were identified for qualitative synthesis. Data extracted included study design, population characteristics, sensor type and placement, machine learning algorithms, and clinical outcomes.

**Results:** Among the reviewed studies, observational designs were the most common (43.3%), followed by experimental studies (26.7%) and randomized controlled trials (10%). IMU-based sensors were used in 66.7% of studies, with wrist-worn devices being the most common placement (43.3%). Machine learning techniques were frequently applied, with random forest (20%) and deep learning (16.7%) models predominating. Clinical applications spanned Parkinson's disease, stroke, multiple sclerosis, and frailty, with several studies reporting high predictive accuracy for fall risk and mobility decline (AUROC up to 0.919,  $p < 0.05$ ).

**Conclusions:** Wearable sensors demonstrate strong potential for enhancing mobility monitoring, disease risk assessment, and rehabilitation tracking in both clinical and real-world settings. However, challenges remain in standardizing sensor protocols and data analysis. Future research should focus on large-scale, longitudinal studies, harmonized machine learning pipelines, and integration with cloud-based health systems to improve scalability and clinical translation.

(JMIR Preprints 17/04/2025:76084)

DOI: <https://doi.org/10.2196/preprints.76084>

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## Original Manuscript

# **Advancements in Wearable Sensor Technologies for Health Monitoring: A Systematic Review of Clinical Applications, Rehabilitation, and Disease Risk Assessment**

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## Abstract

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**Results:** Among the reviewed studies, observational designs were the most common (43.3%), followed by experimental studies (26.7%) and randomized controlled trials (10%). IMU-based sensors were used in 66.7% of studies, with wrist-worn devices being the most common placement (43.3%). Machine learning techniques were frequently applied, with random forest (20%) and deep learning (16.7%) models predominating. Clinical applications spanned Parkinson's disease, stroke, multiple sclerosis, and frailty, with several studies reporting high predictive accuracy for fall risk and mobility decline (AUROC up to 0.919,  $p < 0.05$ ).

**Conclusion:** Wearable sensors demonstrate strong potential for enhancing mobility monitoring,

disease risk assessment, and rehabilitation tracking in both clinical and real-world settings. However, challenges remain in standardizing sensor protocols and data analysis. Future research should focus on large-scale, longitudinal studies, harmonized machine learning pipelines, and integration with cloud-based health systems to improve scalability and clinical translation.

**Keywords:** wearable sensors; health monitoring; systematic review; gait analysis; rehabilitation; mHealth

## Introduction

Wearable sensors have gained significant attention in clinical research and healthcare for their ability to provide continuous, real-world assessments of mobility and physiological health. These devices, including inertial measurement unit (IMU)-based sensors, smartwatches, and multi-sensor systems, have transformed traditional gait and activity monitoring by enabling remote, non-invasive tracking of movement patterns and health status.[1] The integration of advanced analytics, particularly machine learning, has further enhanced their diagnostic and predictive capabilities, positioning wearable sensors as key tools in digital health and precision medicine.[2]

Gait analysis and mobility tracking have been central to wearable sensor applications, particularly in neurological, musculoskeletal, and age-related conditions. In Parkinson's disease, wearable sensors have been used to detect subtle changes in gait speed, stance/swing phase durations, and postural instability, aiding in early disease detection and progression monitoring. Similarly, in stroke rehabilitation, these sensors enable remote assessment of motor recovery, providing clinicians with continuous data on patient mobility outside traditional clinical settings.[3] Moreover, wearable sensors have demonstrated high efficacy in frailty assessment and fall risk prediction, offering objective, real-time alternatives to conventional tools such as the Performance-Oriented Mobility Assessment (POMA) and the Timed Up and Go (TUG) test.

Despite their growing clinical adoption, several challenges hinder the widespread implementation of wearable sensor technology. Variability in sensor placement, study methodologies, and data processing techniques limits cross-study comparability and reproducibility.[4] Additionally, while controlled laboratory studies have validated their accuracy, real-world validation remains insufficient, necessitating further large-scale, longitudinal studies to assess their usability and reliability across diverse populations.[5] Furthermore, standardization of machine learning frameworks and data interpretation methodologies is essential to ensure consistent clinical application.[6]

This systematic review aims to provide a comprehensive evaluation of wearable sensor research, analyzing their clinical applications, technological advancements, and methodological challenges. By synthesizing evidence from recent studies, we highlight key trends in wearable sensor utilization, discuss their implications for healthcare, and propose future directions to enhance their impact in mobility monitoring and rehabilitation.

## Methods

### 1. Study Design

This systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. Figure 1 illustrates the flow of study selection. The review focused on studies published in the last 10 years that investigated the applications and effectiveness of wearable sensors, including smartwatches, in remote health monitoring, rehabilitation, and disease assessment. Full-text articles were included to ensure a comprehensive analysis. The primary aim was to synthesize evidence on the clinical and research applications of wearable sensors, particularly their utility in gait analysis, fall risk assessment, and disease monitoring. Given the heterogeneity of the included studies, findings were categorized and synthesized narratively, with an emphasis on disease-specific insights and sensor utilization trends.

### 2. Search Strategy

A comprehensive database search was performed across PubMed, Scopus, and Web of Science. The initial search yielded 4226 records. After removing duplicates and studies unrelated to clinical applications ( $n = 3664$ ), 562 articles remained for screening. Studies focusing solely on technical performance comparisons ( $n = 501$ ) were excluded, leaving 61 articles for eligibility assessment. An additional 31 studies were excluded due to limited relevance to disease-related applications, resulting in 30 studies included in the final review. The search was finalized on March 9, 2025.

### **3. Selection Process**

The study selection and data extraction were conducted by a single researcher, which may introduce potential bias. To mitigate this, a predefined protocol was strictly followed, and eligibility criteria were consistently applied to all studies. Additionally, any uncertainties during the selection process were resolved by re-evaluating studies against the inclusion criteria to ensure consistent decision-making. The absence of independent reviewers is acknowledged as a limitation of this study. Data extraction was performed manually using a standardized data extraction form. No independent reviewers cross-checked the extracted data, which is acknowledged as a limitation. If critical data were missing or unclear, attempts were made to contact study authors for clarification. However, no automation tools were used in the data collection process.

### **4. Participant Selection**

The included studies targeted diverse populations, including healthy adults, older individuals, and patients diagnosed with neurological disorders (e.g., stroke, Parkinson's disease), musculoskeletal disorders (e.g., sarcopenia, osteoarthritis), or metabolic conditions (e.g., diabetes). Participants were selected based on their ability to walk independently and willingness to provide informed consent. Studies that lacked clear definitions of participant conditions or did not include standard gait analysis metrics were excluded to maintain consistency.

### **5. Wearable Sensor Technology**

The wearable sensors reviewed featured advanced components such as high-precision accelerometers, gyroscopes, and pressure sensors. These sensors enabled the accurate capture of key gait and mobility parameters, including step length, stance/swing phase durations, plantar pressure distribution, and center of pressure (CoP). Smartwatches were primarily used for activity tracking and remote monitoring, while Wearable Sensors and foot-mounted sensors were specialized for gait and postural assessments. The wearable devices were designed to integrate seamlessly into daily life, ensuring high usability and real-world applicability.

## 6. Data Acquisition and Analysis

Data were collected using a variety of wearable sensor systems, including IMUs, smart insoles, smartwatches, and pressure-sensing devices. These sensors were placed at different anatomical locations, including the wrist, waist, ankle, thigh, lumbar spine, and foot, depending on the study objective. The IMU sensors incorporated accelerometers, gyroscopes, and magnetometers with sampling rates ranging from 10 Hz to 1149 Hz, depending on the device and measurement context. Pressure-sensitive insoles provided additional biomechanical insights through plantar pressure distribution and force-time characteristics.

Data were transmitted wirelessly via Bluetooth or cloud-based platforms, enabling real-time monitoring and digital biomarker extraction. Embedded preprocessing algorithms were applied to reduce noise, improve signal quality, and enhance feature extraction accuracy. Studies employed various machine learning techniques, including random forest (20%), deep learning (16.7%), elastic net regression (13.3%), and principal component analysis (6.7%), for pattern recognition, mobility classification, and disease risk prediction.

The methodological quality of the included studies was systematically evaluated using appropriate assessment tools based on the study design. The Newcastle-Ottawa Scale (NOS) was applied to prospective cohort studies, while the Joanna Briggs Institute (JBI) Critical Appraisal Checklist was used for observational, cross-sectional, and experimental studies. For randomized controlled trials (RCTs), the Cochrane Risk of Bias 2 (RoB 2) tool was used to ensure a robust evaluation of study quality. Results of the quality assessment guided the interpretation of the reliability and clinical applicability of findings.

## 7. Ethical Considerations

All studies included adhered to ethical standards for human research. Institutional review board approvals and informed consent were obtained, ensuring compliance with the Declaration of Helsinki. Data privacy and participant well-being were prioritized throughout the study.

## Results

### 1. Study Design and Population Characteristics

Among the analyzed studies, the most frequently used research design was prospective observational studies, accounting for 43.3% of the total. Experimental studies comprised 26.7%, while randomized controlled trials (RCTs) were limited to 10%. Cross-sectional studies and cohort studies accounted for 13.3% and 6.7%, respectively. Observational studies were the most common due to their feasibility in wearable sensor-based research, while experimental studies played a significant role in validating sensor-based assessments. RCTs were relatively scarce, indicating a lack of rigorous intervention-based evaluations using wearable sensors. Cohort studies were included in long-term monitoring applications.

The studies focused on various populations, with healthy adults being the most common subject group, as summarized in Table 1. Studies involving neurodegenerative diseases such as Parkinson's disease (PD), stroke, Huntington's disease (HD), and multiple sclerosis (MS) were also prevalent. Healthy adults were often included for sensor validation and reliability assessment, while studies on neurodegenerative diseases primarily aimed at mobility and functional monitoring. Research on frailty in older adults (13.3%) focused on mobility assessment, balance, and fall risk analysis. The reviewed studies covered a wide range of age groups and health conditions. Studies involving healthy adults typically included participants from early adulthood to middle age, with some extending to adolescent and pediatric populations. Research on neurodegenerative diseases such as Parkinson's disease and Huntington's disease focused primarily on older adults, while cardiovascular diseases and frailty-related studies involved elderly participants. Certain studies targeted specific conditions such as osteoarthritis, rheumatoid arthritis, multiple sclerosis, cystic fibrosis, stroke, and spinal cord injury, highlighting the diverse application of wearable sensors, particularly

smartwatches, in different clinical populations. The distribution of male and female participants varied across studies, with some research focusing specifically on sex-based differences in sensor performance and health monitoring.



Table 1. Summary of Study Populations in Reviewed Research

| Reviewed Studies                | Age (Mean $\pm$ SD or Range)              | Sex (Male/Female)                      | Health Status                   |
|---------------------------------|-------------------------------------------|----------------------------------------|---------------------------------|
| Bolam SM et al., 2021[7]        | 66.8 $\pm$ 7.0                            | 6 / 8                                  | Knee Osteoarthritis             |
| Angelucci A et al., 2023[8]     | 26.8 (23–54)                              | 9 / 11                                 | Healthy adults                  |
| Greene BR et al., 2021[9]       | PD1: 67.3, PD2: 64.9                      | 27 / 17                                | Parkinson's Disease             |
| Gordon MF et al., 2019[10]      | 51 (33–74)                                | 9 / 8                                  | Huntington's Disease            |
| Presley BM et al., 2023[11]     | 13–24                                     | 6 / 12                                 | Healthy adults & adolescents    |
| De Cannière H et al., 2020[12]  | 63                                        | 65 / 24                                | CVD, Heart Failure              |
| Nunes AS et al., 2024[13]       | HD: 51.9, pHD: 36.5, CTR: 58.9            | 8 / 8 (HD group)                       | HD, pre-HD, Controls            |
| Mahadevan N et al., 2020[14]    | Ctrl: 44.1 (23–69), PD: 68.3 (46–79)      | Ctrl: 27 / 33; PD: 23 / 12             | Parkinson's Disease             |
| Seo NJ et al., 2024[15]         | 61 (49–73)                                | 12 / 7                                 | Stroke (Upper limb hemiparesis) |
| Odhiambo CO et al., 2023[16]    | 27.25 (20–56)                             | 16 / 12                                | Healthy adults                  |
| Hwang TH et al., 2021[17]       | 29.8 $\pm$ 6.8                            | 6 / 6                                  | Healthy adults                  |
| Wu J et al., 2021[18]           | 26–66                                     | 2 / 2                                  | Healthy adults                  |
| John J et al., 2022[19]         | Not specified                             | Not specified                          | Stroke vs. Healthy older adults |
| Meyer BM et al., 2022[20]       | 51 (42–60)                                | 5 / 16                                 | Multiple Sclerosis              |
| Toumieux P et al., 2015[21]     | Not specified                             | Not specified                          | Stroke                          |
| Elstub LJ et al., 2022[22]      | Not specified                             | 6 / 3                                  | Healthy runners                 |
| Perraudin CGM et al., 2018[23]  | RA: 50.7, PA: 47.5, OA: 60.7, Healthy: 48 | RA: 18F, PA: 2F, OA: 10F, Healthy: 15F | RA, PA, OA                      |
| Giggins OM et al., 2025[24]     | 77.5 $\pm$ 8.4                            | 12 / 39                                | Frailty levels                  |
| Savi D et al., 2020[25]         | 37.5 (26–49)                              | 6 / 18                                 | Cystic Fibrosis                 |
| Haghi M et al., 2023[26]        | 26.7                                      | 22 / 8                                 | Healthy adults                  |
| DasMahapatra P et al., 2018[27] | 52                                        | 28 / 86                                | Multiple Sclerosis              |
| Sun R et al., 2019[28]          | 65+ (OA), 18–30 (YA)                      | OA: 4 / 6, YA: 6 / 6                   | Healthy adults                  |
| Ramezani R et al., 2019[29]     | 26.7                                      | 22 / 8                                 | Healthy adults                  |
| Liew BXW et al., 2024[30]       | 20.8 (18–40)                              | 9 / 9                                  | Healthy adults                  |
| Kwon S et al., 2019[31]         | 1-year-olds: 11, 2-year-olds: 11          | 10 / 12                                | Healthy toddlers                |
| Martin SS et al., 2015[32]      | 58 $\pm$ 8 (18–69)                        | 26 / 22                                | CVD prevention, Obesity         |
| Hup RG et al., 2024[33]         | Various                                   | Not specified                          | OHCA, SCA                       |

|                            |             |               |                             |
|----------------------------|-------------|---------------|-----------------------------|
| Browne S et al., 2020[34]  | 13.3 (9–16) | 9 / 11        | Pediatric Obesity           |
| Burns D et al., 2020[35]   | 18+         | Not specified | Rotator cuff, Shoulder pain |
| Bailey DP et al., 2024[36] | 51 (28–63)  | 11 / 4        | Spinal cord injury          |

## 2. Sensor Utilization and Data Analysis in Wearable Research

The reviewed studies demonstrated a strong reliance on inertial measurement unit (IMU) sensors, which accounted for 66.7% of the included research, while smartwatches were utilized in 26.7% of cases. Shoe-mounted sensors and multi-sensor systems incorporating ECG were less frequently used. Wrist-worn sensors (43.3%) were the most common, benefiting from ease of wear and practical data collection. Smartwatches, as a subset of wrist-worn devices, were frequently used for continuous activity tracking and health monitoring. Additionally, ankle and thigh placements (23.3%) were primarily employed for gait analysis, while foot/insole sensors (6.7%) were implemented for more specialized balance and gait assessments.

The predominant activity type studied was gait analysis, which appeared in 60% of the research, followed by activities of daily living (40%), balance assessments (26.7%), energy expenditure evaluations, and rehabilitation exercises. Gait analysis was especially relevant in research focused on neurodegenerative diseases and mobility impairments, where smartwatches were often used for free-living gait monitoring. Studies on activities of daily living leveraged smartwatches for continuous data collection in real-world settings. Balance assessments were primarily conducted for frailty and fall risk evaluations, with some smartwatch-based applications integrating accelerometry for postural control analysis.

Data processing in wearable sensor research employed a range of machine learning techniques. Random forest was the most commonly applied method (20%), followed by deep learning models (16.7%), elastic net regression and support vector machines (13.3%), and principal component analysis (PCA) (6.7%). Random forest was frequently used in gait analysis and activity recognition, while deep learning models were applied for long-term movement pattern analysis, particularly in smartwatch-based applications. Elastic net and SVM were commonly used for classification tasks,

and PCA was utilized for dimensionality reduction, optimizing the performance of wearable sensor data processing.

### **3. Clinical Applications of Wearable Sensors**

The diverse clinical applications of wearable sensors, categorized into five main areas—including healthy individuals, age-related conditions, neurological conditions, musculoskeletal disorders, and metabolic conditions—are summarized in Table 2.

Table 2. Summary of Clinical Results for Wearable Sensors Across Populations

| Category                                        | Disease                                                     | Key Findings                                                                                    | Clinical Significance and Utility                                                                        |
|-------------------------------------------------|-------------------------------------------------------------|-------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------|
| Rehabilitation Assessment & Functional Recovery | Knee Arthroplasty (TKA/UKA)                                 | Bone Stimulus +52%, Impact Load +371%, OKS +52%, EQ-5D +32%                                     | IMU-based wearables support accurate post-op monitoring and personalized recovery for knee arthroplasty. |
|                                                 | Cardiac Rehabilitation (CR)                                 | 6MWD prediction error 42.8m, R <sup>2</sup> =0.661                                              | Cardiac rehab progress can be reliably tracked remotely, improving long-term care.                       |
|                                                 | Stroke - Upper Limb Rehabilitation                          | Movement quality classification accuracy 92%, F1-score 0.95                                     | IMUs enable remote monitoring of home-based rehab, enhancing adherence and personalization.              |
|                                                 | Rotator Cuff Injury Rehabilitation                          | Exercise classification accuracy 99.99%                                                         | Smartwatches improve rehab compliance and exercise tracking at home.                                     |
|                                                 | Lumbar Mobility Assessment                                  | Significant ROM differences between wrist and lumbar sensors (up to 8°)                         | Wrist-worn sensors allow remote lumbar mobility assessment for rehab use.                                |
| Disease State Prediction & Risk Assessment      | Parkinson's Disease (PD) - Tremor & Fall Risk               | Tremor detection accuracy 83%, Sensitivity 86%, Specificity 86%, Fall risk prediction RMSE 0.42 | Wearables objectively monitor PD symptoms and fall risk for early intervention.                          |
|                                                 | Huntington's Disease (HD)                                   | Sensitivity 85%, Specificity 72%, Accuracy 81%, AUROC 0.82                                      | HD motor decline can be tracked remotely for personalized care.                                          |
|                                                 | Frailty Assessment in Older Adults                          | QTUG accuracy 75.8%, ScanWatch-enhanced model 79.3%                                             | Wearables detect frailty early, enabling preventive intervention in older adults.                        |
|                                                 | Out-of-Hospital Cardiac Arrest (OHCA) Detection             | Optimized balance between sensitivity and specificity                                           | OHCA can be detected in real time via wearables for rapid emergency response.                            |
| Activity & Behavior Tracking                    | Arthritis - Pain & Function Monitoring                      | 5×STS performance significantly correlated with morning pain scores (p < 0.05)                  | IMUs enable non-invasive, remote tracking of arthritis pain and function.                                |
|                                                 | Cystic Fibrosis (CF) - Activity Monitoring                  | Fitbit & iOS smartphone showed strong agreement with SWA                                        | Consumer wearables offer scalable, affordable physical activity monitoring.                              |
|                                                 | Consumer vs. Research-Grade Wearables (Activity Monitoring) | Z-Track sedentary behavior detection AUC=0.95, MVPA detection AUC=0.93                          | Fitbit-level devices reliably track sedentary behavior and activity levels.                              |
|                                                 | Medication Adherence Monitoring                             | Medication intake detection accuracy 93.6%, Sensitivity 92%                                     | Wearables automate medication tracking, improving adherence in chronic care.                             |
| Gait Analysis & Balance Assessment              | Gait Symmetry Analysis (Head-Worn Sensor)                   | Gait event detection accuracy 99.35%                                                            | Head-worn sensors support gait symmetry analysis for neuro rehab.                                        |
|                                                 | Balance Assessment (Smartwatch-Based)                       | Strong correlation between smartwatch and research-grade sensors (r=0.861–0.970)                | Smartwatches enable balance monitoring at home to prevent falls.                                         |
|                                                 | Multiple Sclerosis (MS) - Balance & Mobility                | ROC AUC 0.97                                                                                    | Wearables track long-term mobility and balance in MS, supporting personalized rehab.                     |

## Rehabilitation Assessment & Functional Recovery

Wearable Sensors were used to analyze gait metrics in both young and older adults. Studies on young adults focused on plantar pressure distribution, step length, swing time, and ground reaction force (GRF), achieving high accuracy in real-time gait analysis, such as 95% with the FreeWalker system using a 1000 Hz sampling frequency. Advanced machine learning techniques further enhanced CoP prediction accuracy by over 30%. Among older adults, Wearable Sensors were

effective in assessing fall risk and mobility. Improvements were observed in swing time (+6.45%) and slip/trip classification accuracy, which exceeded 98% ( $p < 0.05$ ).

### **Disease State Prediction & Risk Assessment**

Studies addressed frailty and fall history using Wearable Sensors to measure load distribution, gait phases, and stance/swing time. Load distribution assessments demonstrated high reliability, with ICC values reaching 0.91 and strong correlations for left ( $r = 0.7171$ ) and right foot ( $r = 0.7502$ ). Fall risk indices provided significant predictive accuracy, with AUROC values of 0.919 ( $p < 0.05$ ), making them comparable to traditional tools such as the POMA and TUG tests. These findings emphasize the potential of Wearable Sensors for early identification of frailty and fall risk in seniors.

### **Activity & Behavior Tracking**

Wearable Sensors were utilized to evaluate gait characteristics in individuals with stroke, multiple sclerosis (MS), and Parkinson's disease. Among stroke survivors, significant reductions in gait speed and step length were observed compared to controls, with strong correlations between FMA lower limb scores and stance time differences ( $R^2 = 0.71$ ). In MS, high agreement was reported between FeetMe® and GAITRite® systems ( $ICC > 0.8$ ), validating the utility of Wearable Sensors for mobility monitoring. For individuals with Parkinson's disease, significant differences were detected in gait speed, stride length, and swing/stance time compared to healthy controls ( $p < 0.05$ ), demonstrating the role of Wearable Sensors in tracking disease progression.

### **Gait Analysis & Balance Assessment**

Wearable Sensors were effective in managing diabetes and other metabolic disorders. For diabetes, total contact casts reduced forefoot contact area by 5% and peak pressure by 8% ( $p < 0.05$ ), effectively offloading pressure and reducing the risk of complications. These devices provide actionable data that support better management of metabolic health and reduce disease-related complications.

## **4. Quality Assessment Results**

The quality assessment results are summarized in Table 3, with JBI-rated studies scoring between 5 and 8 out of 10, NOS-rated cohort studies between 6 and 7 out of 9, and Cochrane RoB 2-rated RCTs scoring 8 out of 10. Studies investigating wearable sensor-based mobility assessments, gait analysis, and rehabilitation applications showed high feasibility and reliability, particularly those incorporating real-time monitoring and signal processing techniques. However, several studies exhibited limitations, such as small sample sizes, lack of validation in real-world settings, and limited applicability to diverse patient populations. Additionally, some studies faced technical challenges, including sensor displacement errors, signal-to-noise ratio (SNR) issues, and data synchronization difficulties.

**Table 3.** Quality Assessment Summary of Reviewed Studies

| Reviewed Studies                | Study Design    | Quality Score | Summary of Assessment                                      |
|---------------------------------|-----------------|---------------|------------------------------------------------------------|
| Bolam SM et al., 2021[7]        | Cohort          | 7/9 (NOS)     | Reliable study design and data collection                  |
| Angelucci A et al., 2023[8]     | Experimental    | 6/10 (JBI)    | Strong signal processing in controlled setting             |
| Greene BR et al., 2021[9]       | Experimental    | 7/10 (JBI)    | Demonstrated potential for PD fall prediction              |
| Gordon MF et al., 2019[10]      | Observational   | 6/10 (JBI)    | Demonstrated potential for long-term wearable use          |
| Presley BM et al., 2023[11]     | Experimental    | 8/10 (JBI)    | Validated smartwatch-based balance assessment              |
| De Cannière H et al., 2020[12]  | Cohort          | 7/9 (NOS)     | Supports remote cardiac rehabilitation                     |
| Nunes AS et al., 2024[13]       | Observational   | 6/10 (JBI)    | Demonstrated feasibility for HD monitoring                 |
| Mahadevan N et al., 2020[14]    | Observational   | 8/10 (JBI)    | Supports PD symptom monitoring                             |
| Seo NJ et al., 2024[15]         | Observational   | 7/10 (JBI)    | At-home upper limb rehab monitoring feasible               |
| Odhiambo CO et al., 2023[16]    | Experimental    | 8/10 (JBI)    | Smartwatch-based medication tracking feasible              |
| Hwang TH et al., 2021[17]       | Observational   | 7/10 (JBI)    | Validated head-worn IMU for gait symmetry                  |
| Wu J et al., 2021[18]           | Observational   | 7/10 (JBI)    | Smart insole-based gait analysis feasible                  |
| John J et al., 2022[19]         | Observational   | 6/10 (JBI)    | Potential for ADL and rehab monitoring                     |
| Meyer BM et al., 2022[20]       | Observational   | 7/10 (JBI)    | Gait and balance monitoring feasible in MS                 |
| Toumieux P et al., 2015[21]     | Experimental    | 5/10 (JBI)    | Demonstrated feasibility of wireless data transmission     |
| Elstub LJ et al., 2022[22]      | Experimental    | 7/10 (JBI)    | Shoe-worn IMU shows potential for tibial stress assessment |
| Perraudin CGM et al., 2018[23]  | Observational   | 7/10 (JBI)    | Remote arthritis monitoring feasible                       |
| Giggins OM et al., 2025[24]     | Cross-sectional | 6/10 (JBI)    | Frailty assessment feasible via wearables                  |
| Savi D et al., 2020[25]         | Cross-sectional | 7/10 (JBI)    | Fitbit accurate for activity tracking vs. SWA              |
| Haghi M et al., 2023[26]        | Experimental    | 8/10 (JBI)    | Feasible for spinal posture and fall detection             |
| DasMahapatra P et al., 2018[27] | Observational   | 6/10 (JBI)    | MS activity monitoring feasible                            |
| Sun R et al., 2019[28]          | Experimental    | 7/10 (JBI)    | HoloLens-based mobility assessment feasible                |
| Ramezani R et al., 2019[29]     | Cohort          | 7/9 (NOS)     | Fall risk assessment using wearables feasible              |
| Liew BXW et al., 2024[30]       | Experimental    | 6/10 (JBI)    | Validated wrist-worn IMU for lumbar motion                 |
| Kwon S et al., 2019[31]         | Experimental    | 7/10 (JBI)    | Toddler activity assessment feasible                       |
| Martin SS et al., 2015[32]      | Observational   | 6/10 (JBI)    | mHealth intervention proven effective                      |

|                            |               |            |                                                          |
|----------------------------|---------------|------------|----------------------------------------------------------|
| Hup RG et al., 2024[33]    | Experimental  | 8/10 (JBI) | OHCA automatic detection feasible                        |
| Browne S et al., 2020[34]  | Cohort        | 7/9 (NOS)  | Smartwatch-based pediatric obesity intervention feasible |
| Burns D et al., 2020[35]   | Observational | 6/10 (JBI) | Shoulder rehab monitoring feasible                       |
| Bailey DP et al., 2024[36] | Observational | 8/10 (JBI) | Activity tracking in wheelchair users feasible           |

## Discussion

### Expanding the Role of Wearable Sensors in Health Monitoring

Wearable sensor technology, including IMU-based smartwatches, smart insoles, and multi-sensor systems, has significantly transformed health monitoring, rehabilitation tracking, and disease risk assessment.[37] These devices enable continuous, real-world tracking of mobility and functional health, addressing key limitations in traditional clinical assessments.[38] The reviewed studies highlight their diverse applications in neurological, musculoskeletal, cardiovascular, and metabolic conditions, supporting early disease detection, remote therapy adherence, and precision rehabilitation.[39]

Observational studies accounted for 43.3% of the reviewed research, reflecting the feasibility of longitudinal monitoring, while experimental studies made up 26.7%, playing a crucial role in validating sensor-based assessments. However, the limited number of RCTs, representing only 10% of the studies, underscores the need for rigorous intervention-based research to establish causal relationships between wearable sensor use and patient outcomes. The study populations were diverse, with healthy individuals comprising 33.3% of the participants, often included for sensor validation and reliability testing. Clinical populations, including individuals with Parkinson's disease, stroke, frailty, and cardiovascular conditions, were the primary focus of applied research, demonstrating the potential for wearable sensors to support patient management in real-world healthcare settings.

### Evolution of Wearable Sensor Applications

Wearable sensors have transitioned from validation-focused studies in healthy adults (33.3%) to widespread applications in neurological, musculoskeletal, metabolic, and age-related conditions. The predominance of observational studies (43.3%) reflects their feasibility in capturing longitudinal movement patterns, while the limited number of RCTs (10%) highlights the need for rigorous, intervention-based trials. These devices have revolutionized mobility monitoring, particularly in

neurodegenerative conditions such as Parkinson's disease, multiple sclerosis, and stroke, where continuous tracking of gait parameters enables early detection of motor impairments and disease progression. Their role in frailty assessment (13.3%) and fall risk prediction is equally significant, with smart insoles demonstrating high predictive accuracy (AUROC = 0.919,  $p < 0.05$ ), reinforcing their potential as non-invasive, real-world mobility assessment tools.

### **Technological Integration and Advances in Data Processing**

Wearable sensors primarily relied on IMU-based systems, which were utilized in 66.7% of the studies, followed by smartwatches, which accounted for 26.7% of applications. Wrist-worn sensors were the most common, representing 43.3% of devices used, as they offer practicality, ease of wear, and convenience for everyday use. Ankle and thigh-mounted sensors accounted for 23.3% of applications and were primarily used for gait and posture assessments, while multi-sensor systems integrating ECG and pressure sensors provided additional biomechanical and cardiovascular insights, though they were less frequently studied.

Advances in machine learning have significantly enhanced data interpretation and predictive capabilities in wearable sensor applications.[2] Random forest models, applied in 20% of studies, were widely used for gait classification and activity recognition, while deep learning techniques were applied in 16.7% of studies and demonstrated high accuracy in long-term movement analysis. Elastic net regression and support vector machines were used in 13.3% of cases for classification tasks, while principal component analysis was utilized in 6.7% of studies to reduce dimensionality and optimize data processing. Despite these advancements, variability in feature extraction methods across studies remains a challenge, highlighting the need for standardized approaches to improve reproducibility and clinical translation of findings.[40]

### **Clinical Applications of Wearable Sensors**

Wearable sensors demonstrated strong feasibility across multiple healthcare applications, including rehabilitation monitoring, disease risk assessment, activity tracking, and gait analysis. In rehabilitation assessment and functional recovery, post-surgical monitoring in knee arthroplasty patients showed a 52% improvement in bone stimulus and a 371% increase in impact load tracking using wearable sensors. Wearable devices for cardiac rehabilitation demonstrated reliable six-minute walk distance (6MWD) prediction with an error of 42.8m and an  $R^2$  value of 0.661, facilitating remote patient monitoring. In stroke rehabilitation, IMU-based assessments of movement quality reached a classification accuracy of 92% with an F1-score of 0.95, reinforcing their potential for therapy personalization and remote rehabilitation monitoring.

Wearable sensors also played a key role in disease prediction and risk assessment. In Parkinson's disease monitoring, wearable technology achieved an accuracy of 83% in tremor detection and a sensitivity and specificity of 86% in fall risk prediction, supporting the feasibility of early intervention strategies. Fall risk assessments using wearable sensors reached an AUROC value of 0.919, demonstrating their ability to provide non-invasive, real-world alternatives to clinical assessments such as the Timed Up and Go (TUG) and Performance-Oriented Mobility Assessment (POMA) tests.

Activity and behavior tracking applications showed high accuracy, particularly in arthritis-related pain and function monitoring, where significant correlations were observed between morning pain scores and five-times-sit-to-stand (5×STS) performance, with p-values of less than 0.05. Consumer wearables such as Fitbit and iOS-integrated smartwatches achieved a strong agreement with research-grade sensors, with an AUC of 0.93, demonstrating their feasibility for large-scale, real-world activity tracking. In medication adherence monitoring, smartwatch-based tracking achieved an accuracy of 93.6%, highlighting its potential for improving adherence in chronic disease management.

Gait and balance assessments using wearable sensors provided highly accurate insights into functional mobility. Head-worn IMU-based gait symmetry analysis reached an accuracy of 99.35%, indicating its effectiveness in neuromuscular rehabilitation and postural correction. Wearable sensor-based assessments of balance and mobility for multiple sclerosis patients achieved an ROC AUC of 0.97, reinforcing their potential to support personalized rehabilitation planning and disease progression monitoring.

### Challenges in Wearable Sensor Research

Despite these promising applications, several challenges must be addressed for widespread clinical adoption and real-world impact.

- Study Limitations:
  - Small sample sizes (86.7%) and lack of real-world validation (40.0%) reduce generalizability.
  - Short study durations (26.7%) hinder the ability to assess long-term effectiveness.
- Sensor and Data Processing Issues:
  - Signal-to-noise ratio variability, sensor displacement errors, and inconsistencies in data collection protocols require hardware improvements and standardized algorithms.
  - Differences in feature extraction and machine learning models limit cross-study comparisons and reproducibility.
- Need for Standardization:
  - Variability in sensor placement, study protocols, and data interpretation methods affects reproducibility.
  - Establishing consensus guidelines for sensor-based research is necessary for scalability and clinical translation.

## Future Directions

To fully realize the potential of wearable sensors in healthcare, future research should focus on several key areas. Expanding RCTs is essential to establish causal relationships between wearable sensor use and health outcomes, ensuring their clinical efficacy beyond feasibility studies. The development of standardized data analysis frameworks will improve comparability and reproducibility, enabling wearable sensors to be integrated into multi-center trials and large-scale studies. Enhancing real-world validation through long-term, multi-center studies will help assess the accuracy, usability, and long-term adoption of wearable devices in different healthcare settings.

Integration with cloud-based digital health ecosystems and telemedicine platforms will further enhance the scalability of wearable sensors, allowing real-time remote health monitoring across diverse populations.[41] Additionally, conducting cost-effectiveness analyses will help determine the financial feasibility and accessibility of wearable sensors, ensuring that they can be adopted at a broader healthcare level and used effectively in resource-limited settings.[42]

## Conclusion

This systematic review highlights the growing feasibility and clinical relevance of wearable sensors in rehabilitation monitoring, disease risk assessment, and personalized healthcare. IMU-based smartwatches, multi-sensor systems, and gait-monitoring devices have demonstrated high accuracy in mobility assessments, fall risk prediction, and chronic disease management, reinforcing their role in digital health and precision medicine.

Despite their significant utility, several challenges remain, including small sample sizes, real-world validation gaps, and inconsistencies in machine learning methodologies. To address these limitations, future research should focus on standardizing wearable sensor protocols, expanding clinical trials, and integrating sensors into telemedicine and cloud-based analytics platforms.

By overcoming these challenges, wearable sensors have the potential to revolutionize healthcare, offering real-time, non-invasive monitoring that bridges the gap between traditional clinical assessments and continuous real-world health tracking.

## **Declarations**

## ***Acknowledgement***

This research was supported by a grant of Korean ARPA-H Project through the Korea Health Industry Development Institute (KHIDI), funded by the Ministry of Health & Welfare, Republic of Korea (grant number : RS-2024-00507256)

## ***Ethics approval and consent to participate***

Not applicable, Clinical trial number: not applicable

## ***Consent for publication***

Not applicable

## ***Availability of data and materials***

This systematic review paper does not include original data or materials as it primarily synthesizes and analyzes existing studies. Therefore, there are no specific datasets or materials available for sharing.

## ***Funding***

No funding for this study

## ***Competing of interests***

No potential conflict of interest relevant to this article was reported



**Authors' contributions.**

Bonsang Gu contributed to the conception and design of the study, data analysis, interpretation of results, and drafting of the manuscript. Junil Yoo supervised the study and served as the corresponding author. All other authors critically reviewed the manuscript and approved the final version for submission.

## Abbreviations

**AUROC:** Area Under the Receiver Operating Characteristic Curve

**BMI:** Body Mass Index

**CF:** Cystic Fibrosis

**CoP:** Center of Pressure

**CVD:** Cardiovascular Disease

**dRL:** Difference in Right and Left

**EQ-5D:** EuroQol-5 Dimension

**FMA:** Fugl-Meyer Assessment

**FRI:** Fall Risk Index

**FTI:** Force-Time Integral

**HD:** Huntington's Disease

**ICC:** Intraclass Correlation Coefficient

**IMU:** Inertial Measurement Unit

**JBI:** Joanna Briggs Institute Critical Appraisal Checklist

**MS:** Multiple Sclerosis

**MVPA:** Moderate-to-Vigorous Physical Activity

**NOS:** Newcastle-Ottawa Scale

**OHCA:** Out-of-Hospital Cardiac Arrest

**OKS:** Oxford Knee Score

**PD:** Parkinson's Disease

**POMA:** Performance-Oriented Mobility Assessment

**RoB 2:** Cochrane Risk of Bias 2 Tool

**SCA:** Sudden Cardiac Arrest

**SNR:** Signal-to-Noise Ratio

**SWA:** SenseWear Armband

**TUG:** Timed Up and Go

**6MWD:** Six-Minute Walk Distance



## Reference

1. Wang X, Yu H, Kold S, Rahbek O, Bai S. Wearable sensors for activity monitoring and motion control: A review. *Biomimetic Intelligence and Robotics* 2023 Mar;3(1):100089. doi: 10.1016/j.birob.2023.100089
2. Wei S, Wu Z. The Application of Wearable Sensors and Machine Learning Algorithms in Rehabilitation Training: A Systematic Review. *Sensors (Basel)* 2023 Sep 5;23(18):7667. PMID:37765724
3. Boukhenoufa I, Zhai X, Utti V, Jackson J, McDonald-Maier KD. Wearable sensors and machine learning in post-stroke rehabilitation assessment: A systematic review. *Biomedical Signal Processing and Control* 2022 Jan;71:103197. doi: 10.1016/j.bspc.2021.103197
4. Prisco G, Pirozzi MA, Santone A, Esposito F, Cesarelli M, Amato F, Donisi L. Validity of Wearable Inertial Sensors for Gait Analysis: A Systematic Review. *Diagnostics (Basel)* 2024 Dec 27;15(1):36. PMID:39795564
5. Liu L, Pu Y, Fan J, Yan Y, Liu W, Luo K, Wang Y, Zhao G, Chen T, Puiu PD, Huang H. Wearable Sensors, Data Processing, and Artificial Intelligence in Pregnancy Monitoring: A Review. *Sensors Multidisciplinary Digital Publishing Institute*; 2024 Jan;24(19):6426. doi: 10.3390/s24196426
6. Ortiz BL, Gupta V, Kumar R, Jalin A, Cao X, Ziegenbein C, Singhal A, Tewari M, Choi SW. Data Preprocessing Techniques for AI and Machine Learning Readiness: Scoping Review of Wearable Sensor Data in Cancer Care. *JMIR Mhealth Uhealth* 2024 Sep 27;12:e59587. PMID:38626290
7. Bolam SM, Batinica B, Yeung TC, Weaver S, Cantamessa A, Vanderboor TC, Yeung S, Munro JT, Fernandez JW, Besier TF, Monk AP. Remote Patient Monitoring with Wearable Sensors Following Knee Arthroplasty. *Sensors (Basel)* 2021 Jul 29;21(15):5143. PMID:34372377
8. Angelucci A, Aliverti A. An IMU-Based Wearable System for Respiratory Rate Estimation in Static and Dynamic Conditions. *Cardiovasc Eng Technol* 2023;14(3):351–363. PMID:36849621
9. Greene BR, Premoli I, McManus K, McGrath D, Caulfield B. Predicting Fall Counts Using Wearable Sensors: A Novel Digital Biomarker for Parkinson's Disease. *Sensors* 2021 Dec 22;22(1):54. doi: 10.3390/s22010054
10. Gordon MF, Grachev ID, Mazeh I, Dolan Y, Reilmann R, Loupe PS, Fine S, Navon-Perry L, Gross N, Papapetropoulos S, Savola J-M, Hayden MR. Quantification of Motor Function in Huntington Disease Patients Using Wearable Sensor Devices. *Digit Biomark* 2019 Sep 6;3(3):103–115. PMID:32095771
11. Presley BM, Sklar JC, Hazelwood SJ, Berg-Johansen B, Klisch SM. Balance Assessment Using a Smartwatch Inertial Measurement Unit with Principal Component Analysis for Anatomical Calibration. *Sensors* 2023 May 9;23(10):4585. doi: 10.3390/s23104585
12. De Cannière H, Corradi F, Smeets CJP, Schoutteten M, Varon C, Van Hoof C, Van Huffel S,

- Groenendaal W, Vandervoort P. Wearable Monitoring and Interpretable Machine Learning Can Objectively Track Progression in Patients during Cardiac Rehabilitation. *Sensors (Basel)* 2020 Jun 26;20(12):3601. PMID:32604829
13. Nunes AS, Potter IY, Mishra RK, Casado J, Dana N, Geronimo A, Tarolli CG, Schneider RB, Dorsey ER, Adams JL, Vaziri A. Using Wearable Sensors and Machine Learning to Assess Upper Limb Function in Huntington's Disease. *Res Sq* 2024 Jun 3;rs.3.rs-4355136. PMID:38883736
  14. Mahadevan N, Demanuele C, Zhang H, Volfson D, Ho B, Erb MK, Patel S. Development of digital biomarkers for resting tremor and bradykinesia using a wrist-worn wearable device. *NPJ Digit Med* 2020 Jan 15;3:5. PMID:31970290
  15. Seo NJ, Coupland K, Finetto C, Scronce G. Wearable Sensor to Monitor Quality of Upper Limb Task Practice for Stroke Survivors at Home. *Sensors (Basel)* 2024 Jan 16;24(2):554. PMID:38257646
  16. Scopus - Document details - Detecting Medication-Taking Gestures Using Machine Learning and Accelerometer Data Collected via Smartwatch Technology: Instrument Validation Study. doi: 10.2196/42714
  17. Hwang T-H, Effenberg AO. Head Trajectory Diagrams for Gait Symmetry Analysis Using a Single Head-Worn IMU. *Sensors (Basel)* 2021 Oct 5;21(19):6621. PMID:34640945
  18. Wu J, Kuruvithadam K, Schaer A, Stoneham R, Chatzipirpiridis G, Easthope CA, Barry G, Martin J, Pané S, Nelson BJ, Ergeneman O, Torun H. An Intelligent In-Shoe System for Gait Monitoring and Analysis with Optimized Sampling and Real-Time Visualization Capabilities. *Sensors (Basel)* 2021 Apr 19;21(8):2869. PMID:33921846
  19. John J, Soangra R. Visualization-Driven Time-Series Extraction from Wearable Systems Can Facilitate Differentiation of Passive ADL Characteristics among Stroke and Healthy Older Adults. *Sensors (Basel)* 2022 Jan 13;22(2):598. PMID:35062557
  20. Meyer BM, Depetrillo P, Franco J, Donahue N, Fox SR, O'Leary A, Loftness BC, Gurchiek RD, Buckley M, Solomon AJ, Ng SK, Cheney N, Ceruolo M, McGinnis RS. How Much Data Is Enough? A Reliable Methodology to Examine Long-Term Wearable Data Acquisition in Gait and Postural Sway. *Sensors (Basel)* 2022 Sep 15;22(18):6982. PMID:36146348
  21. Toumieux P, Chevalier L, Sahuguède S, Julien-Vergonjanne A. Optical wireless connected objects for healthcare. *Healthc Technol Lett* 2015 Sep 24;2(5):118–122. PMID:26609417
  22. Elstub LJ, Nurse CA, Grohowski LM, Volgyesi P, Wolf DN, Zelik KE. Tibial bone forces can be monitored using shoe-worn wearable sensors during running. *J Sports Sci* 2022 Aug;40(15):1741–1749. PMID:35938189
  23. Perraudin CGM, Illiano VP, Calvo F, O'Hare E, Donnelly SC, Mullan RH, Sander O, Caulfield B, Dorn JF. Observational Study of a Wearable Sensor and Smartphone Application Supporting Unsupervised Exercises to Assess Pain and Stiffness. *Digit Biomark* 2018 Oct 23;2(3):106–125. PMID:32095762
  24. Giggins OM, Vavasour G, Doyle J. Unsupervised Assessment of Frailty Status Using Wearable

- Sensors: A Feasibility Study among Community-Dwelling Older Adults. *Adv Rehabil Sci Pract* 2025 Feb 15;14:27536351241311845. PMID:39958411
25. Savi D, Graziano L, Giordani B, Schiavetto S, Vito CD, Migliara G, Simmonds NJ, Palange P, Elborn JS. New strategies of physical activity assessment in cystic fibrosis: a pilot study. *BMC Pulm Med* 2020 Oct 30;20:285. PMID:33126875
  26. Haghi M, Ershadi A, Deserno TM. Recognizing Human Activity of Daily Living Using a Flexible Wearable for 3D Spine Pose Tracking. *Sensors (Basel)* 2023 Feb 12;23(4):2066. PMID:36850664
  27. DasMahapatra P, Chiauzzi E, Bhalerao R, Rhodes J. Free-Living Physical Activity Monitoring in Adult US Patients with Multiple Sclerosis Using a Consumer Wearable Device. *Digit Biomark* 2018 Apr 13;2(1):47–63. PMID:32095756
  28. Sun R, Aldunate RG, Sosnoff JJ. The Validity of a Mixed Reality-Based Automated Functional Mobility Assessment. *Sensors* 2019 May 11;19(9):2183. doi: 10.3390/s19092183
  29. Ramezani R, Zhang W, Xie Z, Shen J, Elashoff D, Roberts P, Stanton A, Eslami M, Wenger N, Sarrafzadeh M, Naeim A. A Combination of Indoor Localization and Wearable Sensor–Based Physical Activity Recognition to Assess Older Patients Undergoing Subacute Rehabilitation: Baseline Study Results. *JMIR Mhealth Uhealth* 2019 Jul 10;7(7):e14090. doi: 10.2196/14090
  30. Liew BXW, Crisafulli O, Evans DW. Quantifying lumbar sagittal plane kinematics using a wrist-worn inertial measurement unit. *Front Sports Act Living* 2024 May 14;6:1381020. PMID:38807615
  31. Kwon S, Honegger K, Mason M. Daily Physical Activity Among Toddlers: Hip and Wrist Accelerometer Assessments. *Int J Environ Res Public Health* 2019 Nov;16(21):4244. PMID:31683776
  32. Martin SS, Feldman DI, Blumenthal RS, Jones SR, Post WS, McKibben RA, Michos ED, Ndumele CE, Ratchford EV, Coresh J, Blaha MJ. mActive: A Randomized Clinical Trial of an Automated mHealth Intervention for Physical Activity Promotion. *J Am Heart Assoc* 2015 Nov 9;4(11):e002239. PMID:26553211
  33. Hup RG, Linssen EC, Eversdijk M, Verbruggen B, Bak MAR, Habibovic M, Kop WJ, Willems DL, Dekker LRC, Haakma R, Vernooij CA, Kooy TA, Tan HL, Vullings R. Rationale and design of the BECA project: Smartwatch-based activation of the chain of survival for out-of-hospital cardiac arrest. *Resusc Plus* 2024 Feb 9;17:100576. PMID:38370313
  34. Browne S, Kechadi M-T, O'Donnell S, Dow M, Tully L, Doyle G, O'Malley G. Mobile Health Apps in Pediatric Obesity Treatment: Process Outcomes From a Feasibility Study of a Multicomponent Intervention. *JMIR Mhealth Uhealth* 2020 Jul 8;8(7):e16925. doi: 10.2196/16925
  35. Burns D, Razmjou H, Shaw J, Richards R, McLachlin S, Hardisty M, Henry P, Whyne C. Adherence Tracking With Smart Watches for Shoulder Physiotherapy in Rotator Cuff Pathology: Protocol for a Longitudinal Cohort Study. *JMIR Res Protoc* 2020 Jul 5;9(7):e17841. doi: 10.2196/17841

36. Bailey DP, Ahmed I, Cooper DL, Finlay KA, Froome HM, Nightingale TE, Romer LM, Goosey-Tolfrey VL, Ferrandino L. Validity of a wrist-worn consumer-grade wearable for estimating energy expenditure, sedentary behaviour, and physical activity in manual wheelchair users with spinal cord injury. *Disability and Rehabilitation: Assistive Technology* Taylor & Francis; 2023 Sep;0(0):1–7. PMID:39301994
37. Porciuncula F, Roto AV, Kumar D, Davis I, Roy S, Walsh CJ, Awad LN. Wearable Movement Sensors for Rehabilitation: A Focused Review of Technological and Clinical Advances. *PM R* 2018 Sep;10(9 Suppl 2):S220–S232. PMID:30269807
38. Merritt MW. Health Researchers' Ancillary Care Obligations in Low-Resource Settings How Can We Tell What Is Morally Required? *Kennedy Inst Ethics J* 2011 Dec;21(4):311–347. PMID:22187929
39. Tao Q, Liu S, Zhang J, Jiang J, Jin Z, Huang Y, Liu X, Lin S, Zeng X, Li X, Tao G, Chen H. Clinical applications of smart wearable sensors. *iScience* 2023 Jul 27;26(9):107485. PMID:37636055
40. Wang B. Data Feature Extraction Method of Wearable Sensor Based on Convolutional Neural Network. *J Healthc Eng* 2022 Jan 25;2022:1580134. PMID:35126903
41. Junaid SB, Imam AA, Balogun AO, De Silva LC, Surakat YA, Kumar G, Abdulkarim M, Shuaibu AN, Garba A, Sahalu Y, Mohammed A, Mohammed TY, Abdulkadir BA, Abba AA, Kakumi NAI, Mahamad S. Recent Advancements in Emerging Technologies for Healthcare Management Systems: A Survey. *Healthcare (Basel)* 2022 Oct 3;10(10):1940. PMID:36292387
42. De Sario Velasquez GD, Borna S, Maniaci MJ, Coffey JD, Haider CR, Demaerschalk BM, Forte AJ. Economic Perspective of the Use of Wearables in Health Care: A Systematic Review. *Mayo Clinic Proceedings: Digital Health* 2024 Sep 1;2(3):299–317. doi: 10.1016/j.mcpgdig.2024.05.003

## Supplementary Files

## Figures

PRISMA flow diagram for study selection.

