Wearable Devices for Remote Monitoring of Chronic Diseases: A Systematic Review

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

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Abstract

Background: Wearable devices enable the remote collection of health parameters, supporting the outpatient plans recommended by the World Health Organization (WHO) to manage chronic diseases. While disease-specific monitoring is accurate, a comprehensive analysis of wearables across various chronic diseases helps to standardize remote patient monitoring (RPM) systems.

Objective: This review aims to identify wearables for remote monitoring of chronic diseases, focusing on (i) wearable devices, (ii) sensor types, (iii) health parameters, (iv) body locations, and (v) medical applications.

Methods: We develop a search strategy and conduct searches across three databases: PubMed, Web of Science, and Scopus. After reviewing 1,160 articles, we select 61 that address cardiovascular, cancer, neurological, metabolic, respiratory, and other diseases. We create a data analysis method based on our five objectives to organize the articles for a comprehensive analysis.

Results: From the 61 articles, 39 use wearable bands such as smartwatches, wristbands, armbands, and straps to monitor chronic diseases. Wearable devices commonly include various sensor types, such as accelerometers (39/61), photoplethysmographic (PPG) sensors (18/61), biopotential meters (17/61), pressure meters (11/61), and thermometers (9/61). These sensors collect diverse health parameters, such as acceleration (39/61), heart rate (24/61), body temperature (9/61), blood pressure (8/61), and peripheral oxygen saturation (SpO?) (7/61). Common sensor body locations are the wrist, followed by the upper arm, and the chest. The medical applications of wearable devices are neurological (21/61) and cardiovascular diseases (15/61). Additionally, researchers apply wearable devices for wellness and lifestyle monitoring (39/61), mostly activity (39/39) and sleep (10/39).

Conclusions: This review underscores that wearable devices primarily function as bands, commonly worn on the wrist, to monitor chronic diseases. These devices collect acceleration, heart rate, body temperature, blood pressure, and SpO?, focusing on neurological disorders and cardiovascular diseases. Our findings establish a baseline for identifying health parameters remotely collected by wearables across various chronic diseases, providing insights for standardizing RPM systems.

(JMIR Preprints 17/03/2025:74071)
DOI: https://doi.org/10.2196/preprints.74071

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Conclusion: This review underscores that wearable devices primarily function as bands, commonly worn on the wrist, to monitor chronic diseases. These devices collect acceleration, heart rate, body temperature, blood pressure, and SpO_2, focusing on neurological disorders and cardiovascular diseases. Our findings establish a baseline for identifying health parameters remotely collected by wearables across various chronic diseases, providing insights for standardizing RPM systems.

Keywords: Wearable, Sensor, Health Parameter, Vital Sign, Body Location, Medical Application, Standardized Terminology

Introduction

Background

According to the World Health Organization (WHO), chronic diseases are long-lasting, noninfectious, and progressively worse over time (1). These include cardiovascular diseases, neurological disorders, cancer, respiratory diseases, and metabolic disorders, which collectively account for 74% of annual global mortality and make them the leading cause of death worldwide (1,2). The burden of chronic diseases extends beyond health, severely straining healthcare resources. The Centers for Disease Control and Prevention (CDC) report that 90% of total healthcare expenditure in the United States of America (USA) addresses individuals with chronic diseases (3). This expenditure encompasses ongoing treatments, regular medical consultations, and other healthcare-related costs (4).

Due to their long-lasting nature and the ongoing commitment to curative health services, healthcare professionals mostly manage chronic diseases on an outpatient basis (5). However, preventable factors related to these chronic diseases lead to sudden death (6). The WHO prioritizes people with chronic diseases and underlines the necessity of creating efficient outpatient treatment strategies (7). Healthcare providers achieve this by remotely monitoring health parameters (8,9). Compared to inpatient healthcare delivery, remote patient monitoring (RPM) systems become a promising option for managing chronic diseases (10,11). RPM systems support early detection by real-time monitoring of health and well-being (12) using wearable devices that integrate one or more sensors to remotely collect relevant health parameters (13–15). This reduces clinic visits and conserves time as well as healthcare resources (16).

Wearable-based RPM systems rely on custom-built sensors to gather and analyze biometric and physiological data (17). Contemporary devices such as smartwatches and fitness trackers have several sensors (18) and often pair with apps. Integrating these wearable devices with cloud platforms facilitates efficient data storage and easy access for healthcare providers. The cloud platforms are Apple HealthKit (19), Google Fit (20), Microsoft Azure Health Data Services (21), Amazon AWS HealthLake (22), and Biofourmis (23). Such technologies offer substantial potential for clinical trials, fostering research advancements and improving patient care.

Current articles on wearable devices highlight their potential in managing chronic diseases. Various sensors, such as accelerometers, gyroscopes, magnetometers, biopotential meters, photoplethysmographic (PPG) sensors, and thermometers, monitor health parameters remotely. These include activity, electrocardiography (ECG), electroencephalography (EEG), electromyography (EMG), heartbeats, heart rate, sleep pattern, and body temperature (24–31).

Currently, wearable devices play a key role in monitoring specific chronic diseases, enhancing the effectiveness of RPM by focusing on disease-specific health parameters. For instance, continuous glucose monitor (CGM) sensors track glucose levels in diabetes management (32), biopotential meters monitor heart rhythms in various conditions (33), and inertial measurement units (IMU) evaluate body movements for diagnosing stroke and neurodegenerative diseases (34,35).

While existing reviews focus on specific aspects of wearable devices for particular chronic diseases or particular study participants, such as chronic disease management in primary care (36) and the role of patient adherence in healthcare plans (37), a significant gap in evidence remains. Specifically, we need to identify all wearable devices and health parameters applied to the broad spectrum of chronic diseases. Given the increasing rates of comorbidity among chronic diseases (38), identifying shared health parameters is critical in developing comprehensive wearable-based RPM systems. This review offers insights into designing wearable devices for remote disease monitoring and standardizing RPM terminologies, enhancing interoperability with digital health systems (39).

Objective

This systematic review explores wearable devices and sensor types for remote monitoring of chronic diseases. Specifically, we answer the following research questions:

1 Which wearable devices monitor chronic diseases?

2 Which sensor types integrate these wearable devices?

3 Which health parameters record these sensors?

4 Where are these sensors located on the human body?

5 Which medical applications support the wearable devices?

Method

This systematic review's design and reporting follow the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Multimedia Appendix 1) (40). We register the protocol in PROSPERO (CRD42023460873).

Information source and search strategy

We develop a search strategy and seek full-text articles published in English between January 2019 and December 2023 across three databases: PubMed, Web of Science, and Scopus. Our search strategy incorporates three standard terms relevant to our topic and objectives: "wearable device," "remote monitoring," and "chronic disease." In (Multimedia Appendix 2), we list all relevant synonyms for each of these keywords. We employ the "AND" operator between the keywords and the "OR" operator within the synonyms to ensure we include synonyms in our search.

Eligibility criteria

To ensure a concentrated analysis of wearable devices for remote monitoring of chronic diseases, we establish the following eligibility criteria.

- *Inclusion*
  - Articles that use wearable devices for the remote monitoring of chronic diseases.
  - Articles that employ sensors for remote collection of health parameters.
  - Original research articles published in peer-reviewed journals.
- *Exclusion*
  - Articles that use unobtrusive, implantable, or non-wearable devices or sensor types.
  - Articles that do not involve remote monitoring or data collection.

- Non-journal publications.
- Review articles.

Data management and extraction

We conduct data extraction through regular communication while reviewing the selected articles' titles, abstracts, and full texts. We engage in thorough discussions to resolve discrepancies or doubts regarding the findings. For data extraction, we use a well-organized spreadsheet (Excel, Microsoft Corporation, Redmond, WA, USA). From each article, we extract the following parameters: names of authors, year of publication, country, study design, wearable device's name and type, integrated sensor types, health parameters, body locations, and medical applications (Table 1).

Standardizes Terminology

We develop a standardized terminology based on existing evidence supplemented by the insights of our research team. Our terminology encompasses five predefined categories: wearable device, sensor type, health parameter, body location, and medical application (Figure 1). We systematically organize the articles by these categories to facilitate a thorough analysis of the available evidence. The following sections detail the rationale and evidence.

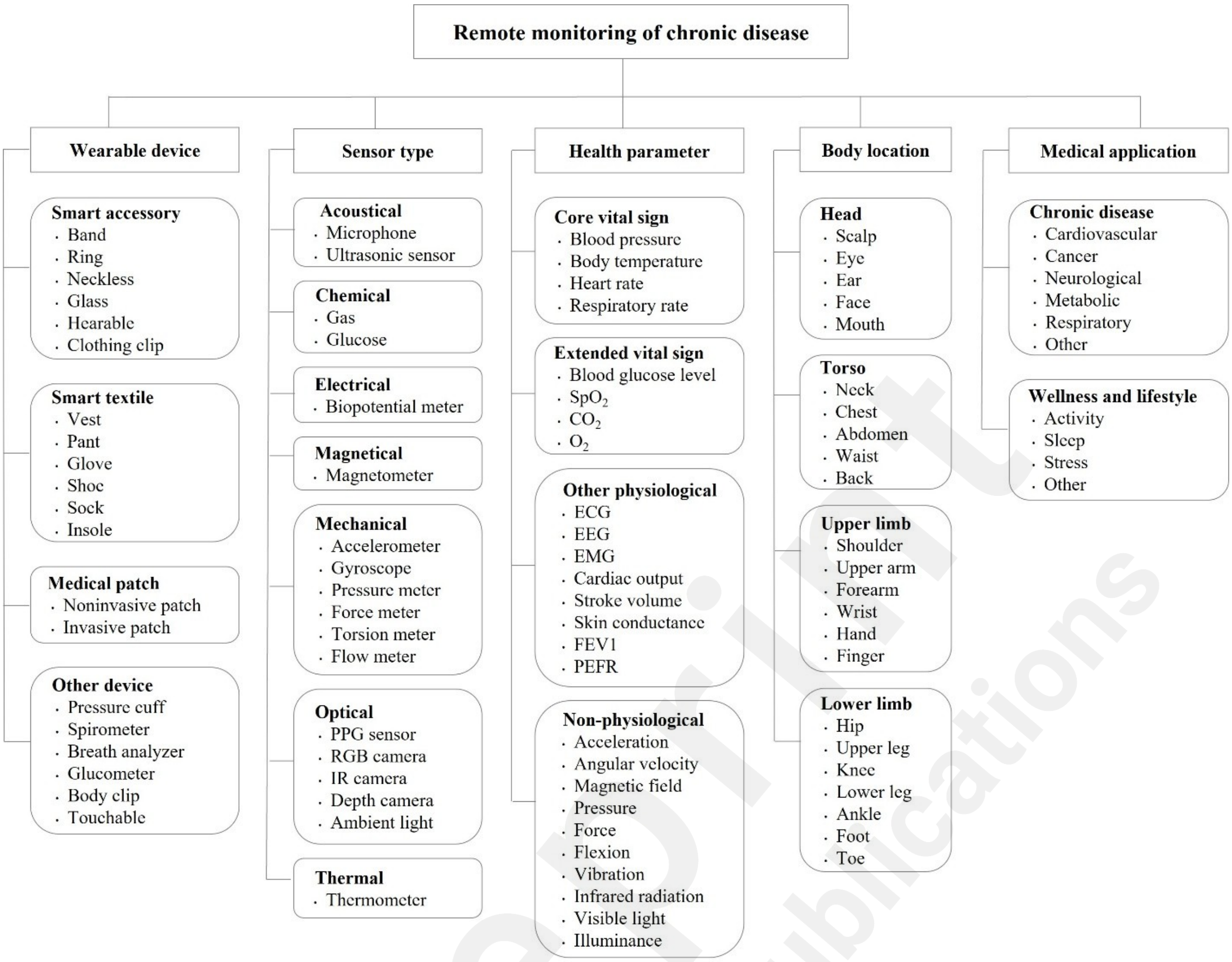

Figure 1. Standardized terminology. *Acronyms:* red, green, blue (RGB), infrared (IR), peripheral oxygen saturation (SpO_2), carbon dioxide (CO_2), oxygen (O_2), forced expiratory volume in the first second (FEV1), peak expiratory flow rate (PEFR).

Wearable device

We categorize wearable devices into smart accessories, smart textiles, medical patches, and other devices (41).

- *Smart accessory*: Wearable device that user wear continuously on the body but do not classify as smart textiles. These devices include bands, rings, necklaces, glasses, hearables, and clothing clips. Our analysis classifies bands as a wide range of wearable devices, including smartwatches, wristbands, armbands, and straps (including belts).
- *Smart textile:* Wearable device that integrates into everyday clothing items such as vests, pants, gloves, shoes, socks, and insoles.
- *Medical patch:* Wearable device with adhesive skin contact or a minimally invasive needle.
- *Other device:* Wearable device that users wear sporadically, perform one-time measurements, and remotely transmit data, such as pressure cuffs, spirometers, breath analyzers,

glucometers, body clips, and touchable devices.

Sensor type

We adopt a sensor classification scheme for sensors utilized in the remote monitoring of chronic diseases, focusing on the different measurements they detect. These are acoustical, chemical, electrical, magnetical, mechanical, optical, and thermal sensors (43).

Health parameter

Health parameters refer to core vital signs, extended vital signs, other physiological data, and non-physiological data.

Body location

We divide the outer body into four regions to specify where sensors position, attach, or where the measurements of health parameters occur. According to Kim, Ock & Kim, we group these regions into head, torso, upper limb, and lower limb (42).

Medical application

The primary application of wearable devices focuses on chronic disease management while optionally offering wellness and lifestyle tracking, which can supplement disease monitoring. After identifying more than ten distinct diseases, we categorize them into five groups based on their physiological systems: cardiovascular (heart disease, hypertension), cancer, neurological (stroke, epilepsy, neurodegenerative disorders, peripheral neuropathy), metabolic (diabetes, obesity), respiratory (asthma, chronic obstructive pulmonary disease, COPD), and other diseases (44,45). This approach allows us to focus on the broader application of wearable devices across various diseases beyond solely focusing on specific conditions.

Quality appraisal

Our review includes various study designs: observation, development and validation, usability and feasibility, experiment, and pilot and mixed-method studies. As a result, we assess the quality of the articles using the quality assessment with diverse studies (QuADS) (46). The QuADS includes 13 criteria rated on a scale from 0 to 3 (0 = No mention at all, 1 = Very limited, 2 = Somewhat detailed, 3 = Highly detailed), with a total quality score ranging from 0 to 39 (Multimedia Appendix 3).

Results

Identified articles

We identify 1,160 articles from the three electronic databases. After removing duplicates, we consider 812 articles for title and abstract screening and exclude 586. From the 226 articles screened, 18 are unavailable in full text. We thoroughly assess 208 full-text articles for eligibility and exclude 147 that do not meet the inclusion and exclusion criteria. Finally, we include 61 articles (Figure 2).

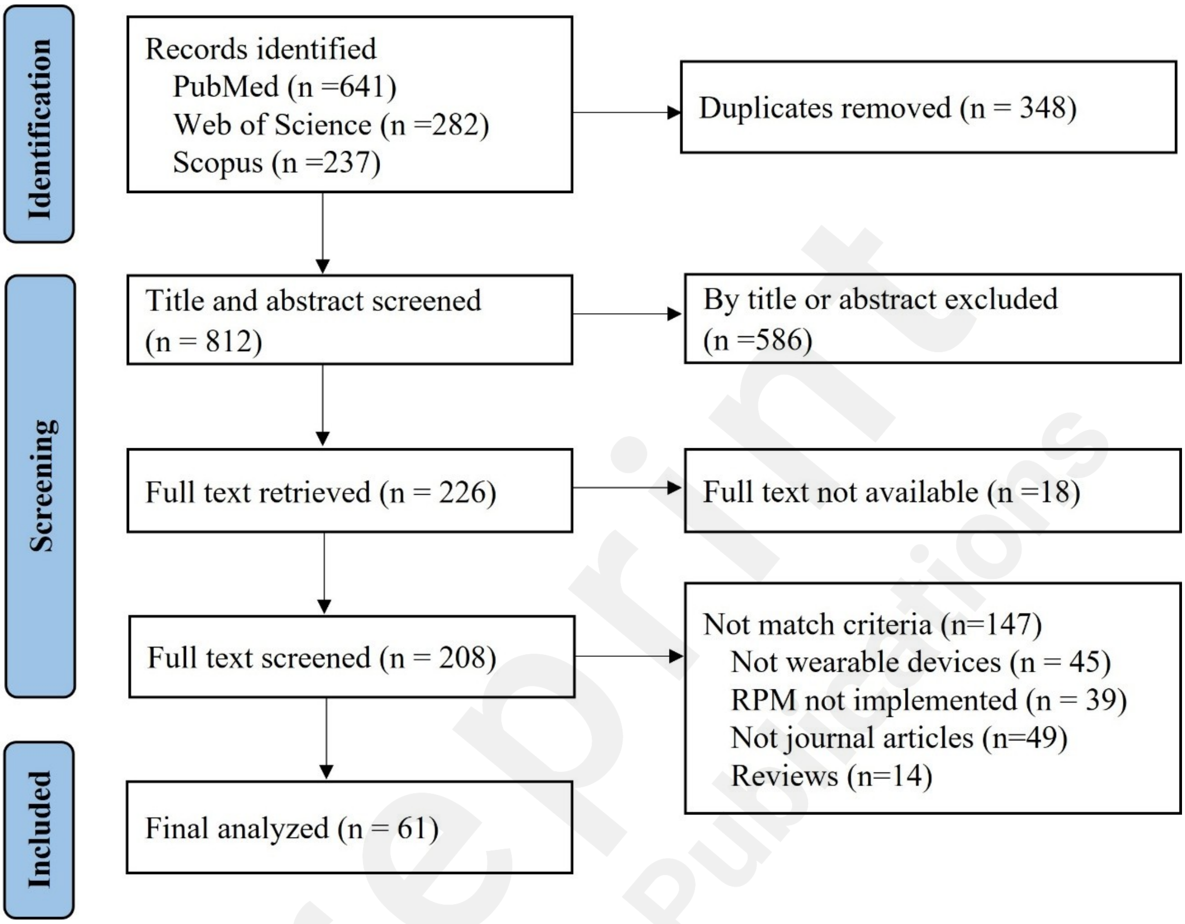

Figure 2. PRISMA flow chart.

Characteristics of articles

The included articles span 21 countries, with the USA leading with 19, followed by Italy with six, and the United Kingdom with five. We identify various study designs, with 34 observations comprising the largest group. Additionally, 15 focus on system development, validation, usability, and feasibility, while seven are experiments, three are pilot studies, and two are mixed-method studies (Table 1).

Table 1. The list of articles included in this review (N=61)

Reference, Year	Country	Study design	Devices name	Device type	Sensor type	Health parameter	Body location	Medical application	
								Chronic diseases	Wellness and lifestyle
Chi (73), 2021	USA	Pilot	VitalPatch	Noninvasive patch	Biopotential meter, accelerometer, thermometer	ECG, heart rate, respiratory rate, acceleration, body temperature	Chest	Cardiovascular	Activity, sleep
Stehlik (72),2020	USA	Observational	VitalPatch	Noninvasive patch	Biopotential meter, accelerometer, thermometer	ECG, heart rate, respiratory rate, acceleration, body temperature	Chest	Cardiovascular	Activity, sleep
Sohn (65), 2020	USA	Pilot	Fitbit Charge 2	Band	PPG sensor, accelerometer	Heart rate, acceleration	Wrist	Cardiovascular	Activity, sleep
Bleda (88), 2019	Spain	Development and validation	e-Health device	Touchable	Biopotential meter	ECG	Finger	Cardiovascular	N/A
				Pressure cuff	Pressure meter	Blood pressure	Upper arm		
Blockhaus (87), 2021	Germany	Observational	LifeVest	Vest	Biopotential meter, accelerometer	ECG, heart rate, acceleration	Chest	Cardiovascular	Activity, other**
Wong (70),2022	Hong Kong	Pilot	Everion	Band	PPG sensor, accelerometer, thermometer	Heart rate, SpO_2, respiratory rate, acceleration, body temperature	Upper arm	Cardiovascular	Activity
Ho (90), 2021	Canada	Observational	N/S	Pressure cuff	Pressure meter	Blood pressure	Upper arm	Cardiovascular	N/A
				Body clip	PPG sensor	Heart rate, SpO_2	Finger		
Werhahn (69),2019	Germany	Observational	Apple Watch	Band	PPG sensor, accelerometer	Heart rate, acceleration	Wrist	Cardiovascular	Activity
Santala (33),2022	Finland	Observational	Firstbeat Bodyguard 2, Faros 360	Noninvasive patch	Biopotential meter	ECG, heart rate	Chest	Cardiovascular	N/A
Ausín (74),2023	Spain	Development and validation	N/S	Noninvasive patch	Biopotential meter	Cardiac output, stroke volume	Chest, upper arm	Cardiovascular	N/A
Kovacs (89),2021	Switzerland	Observational	LifeVest	Vest	Biopotential meter, accelerometer	ECG, heart rate, acceleration	Chest	Cardiovascular	Activity, other**
Weng (67),2021	USA	Observational	Apple Watch	Band	PPG sensor	Heart rate	Wrist	Cardiovascular	N/A
Campo (68),2022	France	Observational	ScanWatch	Band	Biopotential meter	ECG	Wrist	Cardiovascular	N/A
Vaseekaran (66),	Germany	Observational	Omron HeartGuide,	Band	Pressure meter	Blood pressure	Wrist	Cardiovascular	N/A

2023			Smart Wear						
Lee (71), 2023	Malaysia	Observational	Huawei Watch	Band	Pressure meter	Blood pressure	Wrist	Cardiovascular	N/A
Peterson (83), 2022	USA	Feasibility	N/S	Pressure cuff	Pressure meter	Blood pressure	Upper arm	Cancer	Activity
			BioHarness	Band [#]	Biopotential meter	ECG, heart rate	Chest		
			AwareTech Action Tracker	Band [#]	Accelerometer	Acceleration	Waist		
Pavica (76),2019	Switzerland	Observational	Everion	Band	PPG sensor, biopotential meter, accelerometer, thermometer	Heart rate, SpO_2, skin conductance, acceleration, body temperature	Upper arm	Cancer	Stress, activity
Lévi (79),2020	United Kingdom	Observational	Thoracic sensor	Noninvasive patch	Accelerometer [#]	Acceleration [#]	Chest	Cancer	Activity, sleep
			Actigraph	Band	Accelerometer [#]	Acceleration [#]	Wrist		
Wu (84),2019	Taiwan	Observational	Apple Watch, Samsung Gear S2	Band	PPG sensor, accelerometer	Heart rate, acceleration	Wrist	Cancer	Activity
Ghods (82), 2021	USA	Observational	Misfit Shine AT	Band	Accelerometer	Acceleration	Wrist	Cancer	Activity
Pavic (80), 2020	Switzerland	Observational	Everion	Band	PPG sensor, biopotential meter, accelerometer, thermometer	Heart rate, SpO_2, skin conductance, acceleration, body temperature	Upper arm	Cancer	Stress, activity
Ayyoubzadeh (77), 2023	Iran	Development and usability	N/S	Band	PPG sensor, thermometer	Heart rate, body temperature	Wrist	Cancer	N/A
Filakova (75), 2023	Czech Republic	Nonrandomized trial	Polar M430	Band	PPG sensor	Heart rate	Wrist	Cancer	N/A
Chung (81),2019	Republic of Korea	Observational	Fitbit Charge HR	Band	Accelerometer	Acceleration	Wrist	Cancer	Activity, sleep
Ha (78),2022	Australia	Feasibility	GENEActiv	Band	Accelerometer	Acceleration	Wrist	Cancer	Activity
Gao (34), 2023	USA	Randomized controlled trial	Fitbit Charge 5	Band	Accelerometer	Acceleration	Wrist	Cancer	Activity
Albani (29), 2019	Italy	Nonrandomized trial	Shimmer3 IMU	Band	Accelerometer, gyroscope, magnetometer	Acceleration, angular velocity, magnetic field	Chest, upper & lower leg	Neurological	Activity
Ruokolainen (24), 2022	Finland	Observational	Movesense	Band	Accelerometer, gyroscope, magnetometer	Acceleration, angular velocity, magnetic field	Wrist	Neurological	Activity
			Forciot smart insole	Insole	Pressure meter	Force	Foot		
Lipsmeier (49),2022	Switzerland	Observational	Moto 360	Band	Accelerometer	Acceleration	Wrist	Neurological	Activity
Gatsios (52),2020	Italy, Greece, United Kingdom	Randomized controlled trial	Microsoft Band	Band	Accelerometer [#], gyroscope, PPG sensor, biopotential meter, thermometer	Acceleration [#], angular velocity, heart rate, skin conductance, body temperature	Wrist	Neurological	Activity, sleep, stress
			Moticon insole	Insole	Accelerometer [#], force meter, pressure meter	Acceleration [#], force, pressure	Foot		

Ravichandran (27), 2023	USA	Development and validation	Itex glove	Glove	Torsion meter, accelerometer, gyroscope	Flexion, acceleration, angular velocity	Hand	Neurological	Activity
Lee (51), 2023	USA	Feasibility	LSM9DS1 Breakout	Band	Accelerometer, gyroscope, magnetometer	Acceleration, angular velocity, magnetic field	Waist	Neurological	Activity
Blanc (35),2022	France	Observational	Beyond Your Motion SAS	Band	Accelerometer, gyroscope	Acceleration, angular velocity	Upper arm	Neurological	Activity
Huo (53),2020	United Kingdom	Development and validation	N/S	Touchable	Force meter	Force	Hand	Neurological	Activity
				Band	Accelerometer, gyroscope, magnetometer	Acceleration, angular velocity, magnetic field, vibration	Forearm, upper arm		
Sharma (55),2023	USA	Observational	LEGSys	Band	Accelerometer, gyroscope, magnetometer	Acceleration, angular velocity, magnetic field	Upper & lower leg, waist	Neurological	Activity
Sigcha (48),2023	Spain, Portugal	Observational	TickWatch S2	Band	Accelerometer	Acceleration	Wrist	Neurological	Activity
Zedda (25),2023	Italy	Feasibility	MuSe sensors	Band	Accelerometer, gyroscope, magnetometer	Acceleration, angular velocity, magnetic field	Wrist	Neurological	Activity
Toh (57),2023	Hong Kong	Mixed method	N/S	Band	Accelerometer, gyroscope	Acceleration, angular velocity	Wrist	Neurological	Activity
Marin-pardo (26), 2021	USA	Development	Myoware 2	Noninvasive patch	Biopotential meter	EMG	Forearm	Neurological	N/A
Noorian (86),2019	USA	Observational	Xperteye	Glass	RGB camera	Visible light	Eye	Neurological	N/A
Guo (54),2023	China	Randomized controlled trial	N/S	Band	Accelerometer [#], gyroscope [#], magnetometer [#]	Acceleration [#], angular velocity [#], magnetic field [#]	Upper arm, upper & lower leg	Neurological	Activity
				Glove	Torsion meter, accelerometer [#], gyroscope [#], magnetometer [#]	Flexion, acceleration [#], angular velocity [#], magnetic field [#]	Hand		
Darcy (85),2023	USA	Nonrandomized trial	iStride	Shoe	Accelerometer [#], gyroscope [#]	Acceleration [#], angular velocity [#]	Foot [#]	Neurological	Activity
			Moterum sensor	Clothing clip	Accelerometer [#], gyroscope [#]	Acceleration [#], angular velocity [#]	Foot [#], waist		
Chae (56),2020	Republic of Korea	Observational	N/S	Band	Accelerometer, gyroscope	Acceleration, angular velocity	Wrist	Neurological	Activity
Shivaraja (94),2023	Malaysia	Development and feasibility	16-channel ambulatory dry electrode	Noninvasive patch	Biopotential meter	EEG	Scalp	Neurological	N/A
Frankel (95),2021	USA	Observational	Epilog sensors, Single channel wired electrode	Noninvasive patch	Biopotential meter	EEG	Scalp	Neurological	N/A
Scholten	USA	Observational	N/S	Sock	Thermometer	Body temperature	Foot	Neurological	N/A

(28), 2022									
Waddell (50), 2022	USA	Observational	Fitbit Inspire HR	Band	Accelerometer	Acceleration	Waist, wrist	Neurological	Activity
Ramesh (63), 2021.	United Arab Emirates	Observational	iHealth Glucometer	Glucometer	Glucose	Blood glucose level	Finger [#]	Metabolic	Activity
			Huawei GT2	Band	Accelerometer, gyroscope, PPG sensor [#]	Acceleration, angular velocity, heart rate	Wrist		
			iHealth Pulse Oximeter	Body clip	PPG sensor [#]	SpO_2	Finger [#]		
			iHealth Blood Pressure Monitor	Pressure cuff	Pressure meter	Blood pressure	Upper arm		
Boscari (58),2021	Italy	Observational	Free Style Libre FGM, Dexcom CGM	Invasive patch	Glucose	Blood glucose level	N/S	Metabolic	N/A
Bergenstal (32), 2021	USA	Observational	Dexcom CGM	Invasive patch	Glucose	Blood glucose level	N/S	Metabolic	N/A
Cappon (61),2022	Italy	Development and validation	Dexcom CGM	Invasive patch	Glucose	Blood glucose level	Upper arm	Metabolic	Activity, sleep
			Apple Watch, Fitbit	Band	Accelerometer, gyroscope, PPG sensor	Acceleration, angular velocity, heart rate	Wrist		
Notemi (60),2022	France	Observational	Medtronic CGM with Eenlite glucose	Invasive patch	Glucose	Blood glucose level	Abdomen	Metabolic	N/A
Forlenza (59), 2019	USA	Randomized controlled trial	Dexcom CGM	Invasive patch	Glucose	Blood glucose level	Abdomen	Metabolic	N/A
Beach (96),2021	United Kingdom	Observational	N/S	Insole	Thermometer	Body temperature	Foot	Metabolic	N/A
Kytö (62),2023	Finland	Mixed method	Medtronic CGM with Eenlite glucose	Invasive patch	Glucose	Blood glucose level	Upper arm	Metabolic	Activity, stress, sleep
			Garmin Vivosmart 3	Band [#]	Accelerometer [#], PPG sensor, pressure meter, ambient light	Acceleration [#], heart rate [#], pressure, illuminance	Wrist [#]		
			Exsed	Band [#], clothing clip	Accelerometer [#], gyroscope	Acceleration [#], angular velocity	Wrist [#], waist		
			Firstbeat Bodyguard 2	Noninvasive patch	Accelerometer [#], biopotential meter	Acceleration [#], heart rate [#], respiratory rate	Chest		
Knijffa (30), 2022	Netherlands	Observational	Steel HR smartwatch	Band	Accelerometer, PPG sensor	Acceleration, heart rate	Wrist	Metabolic	Activity, sleep
			Withings Blood Pressure Monitor	Pressure cuff	Pressure meter	Blood pressure	Upper arm		
Lee (64),2019	Republic of Korea	Observational	WELT smart belt	Band	Magnetometer, accelerometer	Magnetic field, acceleration	Waist	Metabolic	Activity, other**
Bui	USA	Development	Asma-1	Spirometer	Flow meter	FEV1, PEFR	Mouth	Respiratory	Activity

(92),2020		and usability	spirometer						
			Moto 360	Band	Accelerometer, gyroscope, PPG sensor	Acceleration, angular velocity, heart rate	Wrist		
Radogna (97),2020	Italy	Development and feasibility	N/S	Breath analyzer	Gas	End-tidal CO_2, end-tidal O_2	Mouth	Respiratory	N/A
Althobiani (91),2023	United Kingdom	Observational	AirNext spirometer	Spirometer	Flow meter	FEV1, PEFR	Mouth	Respiratory	Sleep, stress, activity
			Garmin vivoactive 4	Band	PPG sensor #, accelerometer, gyroscope	SpO_2 #, respiratory rate, heart rate #, acceleration, angular velocity	Wrist		
			N/S	Body clip	PPG sensor#	SpO_2 #, heart rate #	Finger		
Morales-botello (93), 2021	Spain	Usability and validation	EC-12RM Cardioscopy Mobile	Noninvasive patch	Biopotential meter	ECG, heart rate #	Chest	Other*	N/A
			Nonin Onyx Finger Pulse Oximeters	Body clip	PPG sensor	SpO_2, heart rate #	Finger		
			iHealth Blood Pressure Monitor	Pressure cuff	Pressure meter	Blood pressure, heart rate #	Upper arm		

Note:

- We only list sensors that are used; the devices may have additional sensors.
- *#:* Two devices use the same sensor to measure the same parameter. We consider them redundant for the device-sensor-disease mapping but count them as single occurrence.
- *Other*:* Refers to articles that include participants with both cardiovascular and respiratory diseases.
- *Other**:* Refers to additional wellness and lifestyle parameters (e.g., waist circumference measurement, wearing compliance tracking).
- *N/A:* Not applicable.
- *N/S:* Not specified.

Wearable device

We identify 16 distinct wearable devices for remote monitoring of chronic diseases (Figure 3). Bands, noninvasive patches, and pressure cuffs emerge as the most frequently used devices across various chronic diseases, appearing in 39, ten, and six articles, respectively. Neurological disease monitoring uses nine devices, with bands being the most common (24,25,54–57,35,47–53). Researchers employ eight distinct wearable devices for metabolic diseases, with invasive patches (32,58–62) exclusive to this category and the most frequently used, followed by bands (30,61–64). Cardiovascular monitoring involves six wearable devices, primarily bands (65–71) and noninvasive patches (33,72–74). For cancer monitoring, the articles almost exclusively report about bands (34,75,84,76–83).

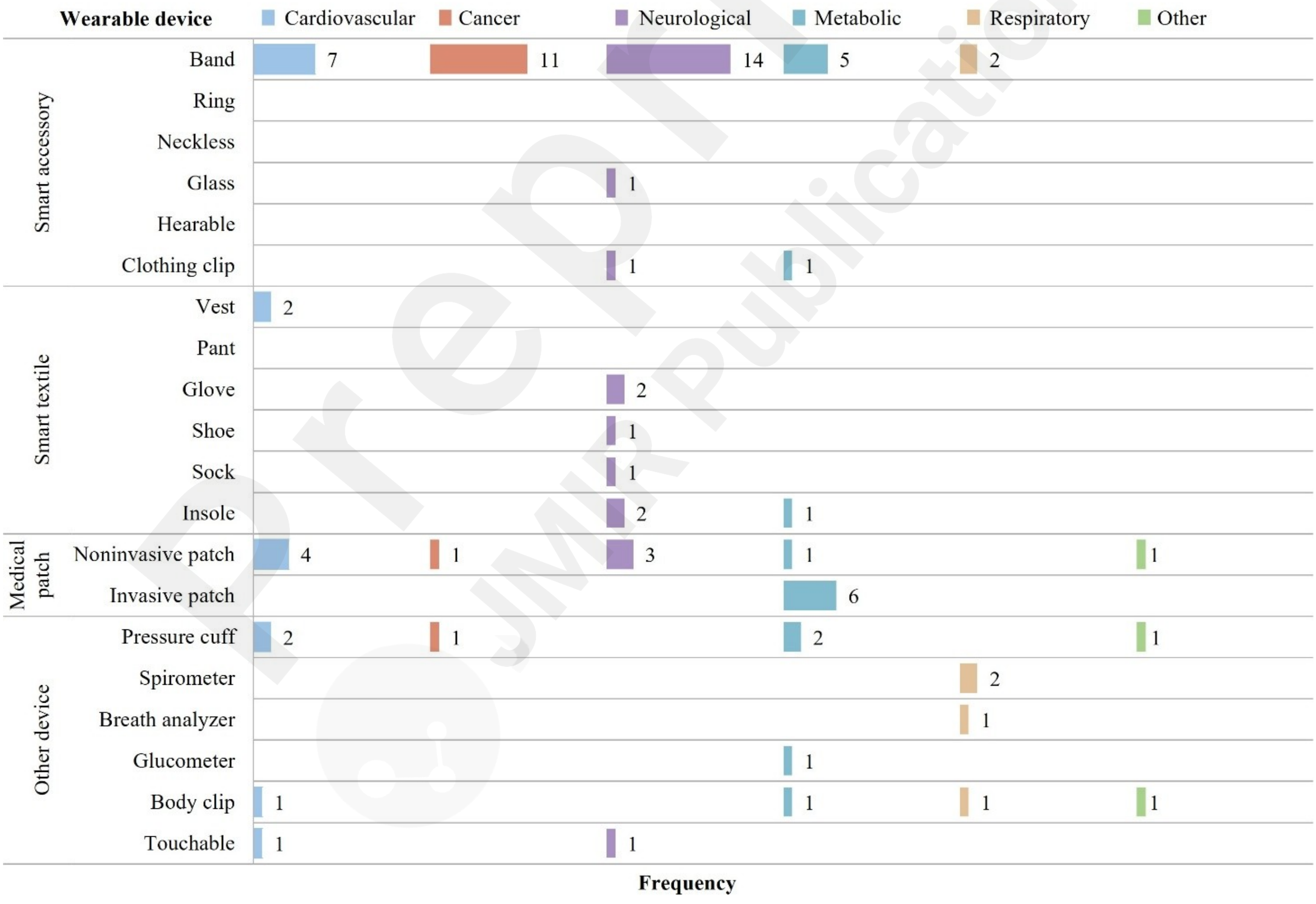

Figure 3. Occurrence of wearable devices across various chronic diseases. Rows represent the number of articles (out of 61) that use each wearable device; columns (disease categories) may exceed the total article count because articles use multiple devices.

Sensor type

The wearable devices feature 14 sensor types. Accelerometers, PPG sensors, biopotential meters, pressure meters, and thermometers are most frequently monitor chronic conditions, appearing in 39, 18, 17, 11, and 9 articles. The wearable devices typically monitor neurological diseases using a diverse array of ten sensors, preferring accelerometers (24,25,53–57,85,27,35,47–52), gyroscopes (24,25,56,57,85,27,35,47,51–55), and magnetometers (24,25,47,51,53–55). Researchers use force meters (52,53), torsion meters (27,54), and wearable cameras (86) exclusively for neurological diseases.

We identify sensors like biopotential meters (33,68,72–74,87–89), accelerometers (65,69,70,72,73,87,89), PPG sensors (65,67,69,70,90), pressure meters (66,71,88,90), and thermometers (70,72,73) as key sensors for the remote monitoring of cardiovascular diseases, ranked by their usage frequency. Similarly, we identify that these sensors monitor cancer, although their frequency varies. Accelerometers (34,76,78–84), PPG sensors (75–77,80,84), biopotential meters (76,80,83), thermometers (76,77,80), and pressure meters (83) are the most common. Additionally, our analysis shows that the articles use glucose sensors (32,58–63) exclusively and frequently for monitoring metabolic diseases (Figure 4).

Figure 4. Occurrence of sensors across various chronic diseases (N=61). Rows represent articles (out of 61) that use each sensor; columns (disease categories) may exceed the total article count because articles use multiple sensors.

Wearable device, sensor type, and chronic disease mapping

A Sankey diagram visually illustrates the relationships between wearable devices, sensor type, and the corresponding chronic disease they monitor (Figure 5). Bands have emerged as the most widely used wearable devices, integrating eight sensor types. They primarily incorporate accelerometers (24,25,54–57,35,47–53), gyroscopes (24,25,57,35,47,51–56), and magnetometers (24,25,47,51,53–55) to facilitate remote monitoring of neurological diseases. They also often feature PPG sensors (30,52,76,77,80,84,91,92,61–63,65,67,69,70,75) and biopotential meters (68,83) to track heart rate and ECG. Moreover, bands are increasingly equipped with other sensor types like electrodermal activity (EDA) biopotential meter (52,76,80), skin thermometer (52,70,76,77,80), oscillometric blood pressure meter (66,71), barometric altimeters (62), and ambient light sensors (62), enabling remote monitoring of skin conductance, body temperature, blood pressure, atmospheric pressure, and illumination, respectively.

Noninvasive medical patches incorporate accelerometers (62,72,73,79) and thermometers (72,73), in addition to the common types of biopotential meters like ECG (33,62,72,73,93), EEG (94,95), EMG (26), and impedance (74). Notably, glucose sensors are the only sensor type integrated into minimally invasive devices (32,58–62). Furthermore, traditional pressure cuffs, like the blood pressure monitors iHealth (iHealth Labs Inc, Sunnyvale, CA, USA) (63,93) and Withings (Withings, Issy-les-Moulineaux, France) (30), now transmit their data remotely. Additionally, pulse oximeters such as iHealth (iHealth Labs Inc, Sunnyvale, CA, USA) (63) and Onyx (Nonin Medical Inc, Plymouth, MN, USA) (93) enhance the functionality of traditional body clips by enabling the remote transmission of SpO_2 and heart rate data.

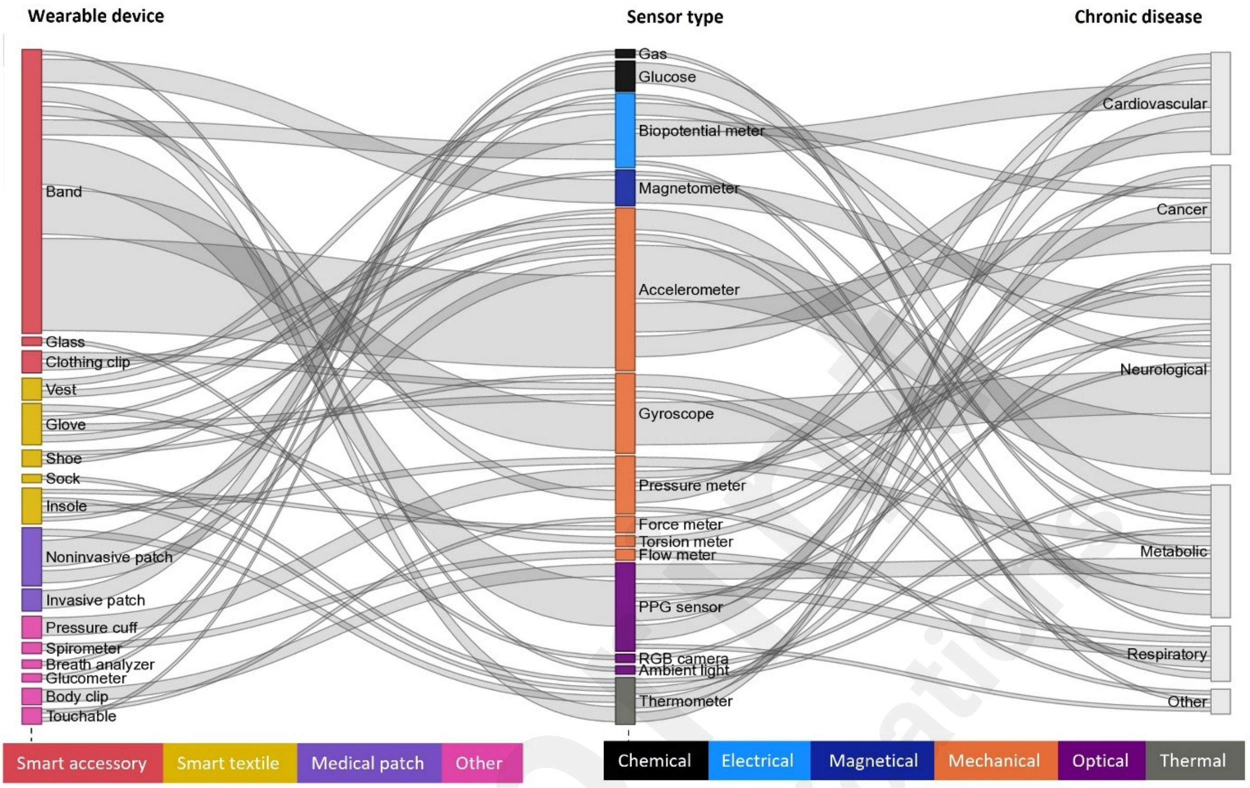

Figure 5. Wearable device, sensor, and disease mapping. Node and link width reflect the match frequency, and the node colors correspond to the wearable device and sensor type.

Health parameter

Sensors gather in total 25 health parameters for remote monitoring of chronic diseases (Figure 6). Acceleration emerges as a key health parameter for monitoring various chronic diseases, as indicated in 39 articles. Specifically, it is the most commonly collected health parameter in the remote monitoring of neurological diseases (24,25,53–57,85,27,35,47–52) and cancer (34,76,78–84).

The articles consistently report on monitoring heart rate, body temperature, blood pressure, and SpO_2, as reported in 24, 9, 8, and 7 articles, respectively. These core and extended vital signs emerge as essential health parameters for the remote monitoring of cardiovascular diseases, cancer, and metabolic diseases. On the other hand, articles primarily monitor neurological diseases using non-physiological parameters. Furthermore, metabolic monitoring focuses on core and extended vital signs and non-physiological parameters (Figure 6).

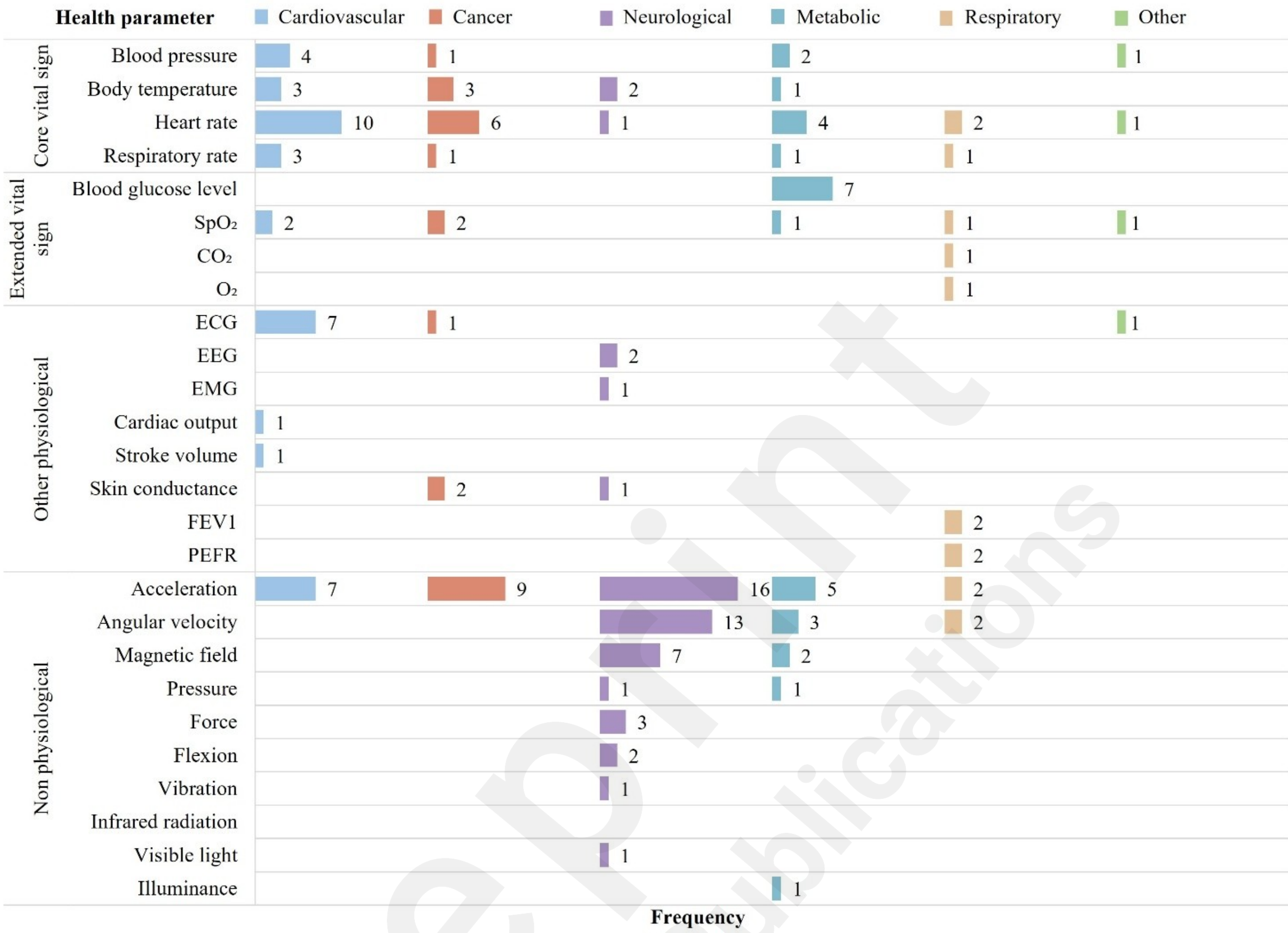

Figure 6. Occurrence of health parameters across various chronic diseases. Rows represent the number of articles (out of 61) that collect each health parameter; columns (disease categories) may exceed the total article count because articles collect multiple health parameters.

Body location

The wrist is the most-frequent body location for sensor placement, comprising eight sensor types. A Sankey diagram illustrates the linkage between accelerometers, PPG sensors, and gyroscopes to the wrist, highlighting that these sensor types mostly position on the wrist (Figure 7). The upper arm is the second-most frequent body location, comprising eight sensor types, with pressure meters (30,63,83,88,90,93) and accelerometers (35,53,54,70,76,80) mount there. The chest is the third-most body location, accommodating five sensor types. Researchers commonly place biopotential meters (33,62,72,73,87,93) here to monitor cardiovascular diseases. Additionally, the waist is the ideal location for IMU sensors, which include accelerometers (50,51,55,62,64,83,85), gyroscopes (51,55,62,85), and magnetometers (51,55,64) for monitoring neurological, metabolic, and cancer diseases. Furthermore, researchers place various sensors on the hand, forearm, upper, and lower leg to monitor neurological diseases (26,27,47,53–55).

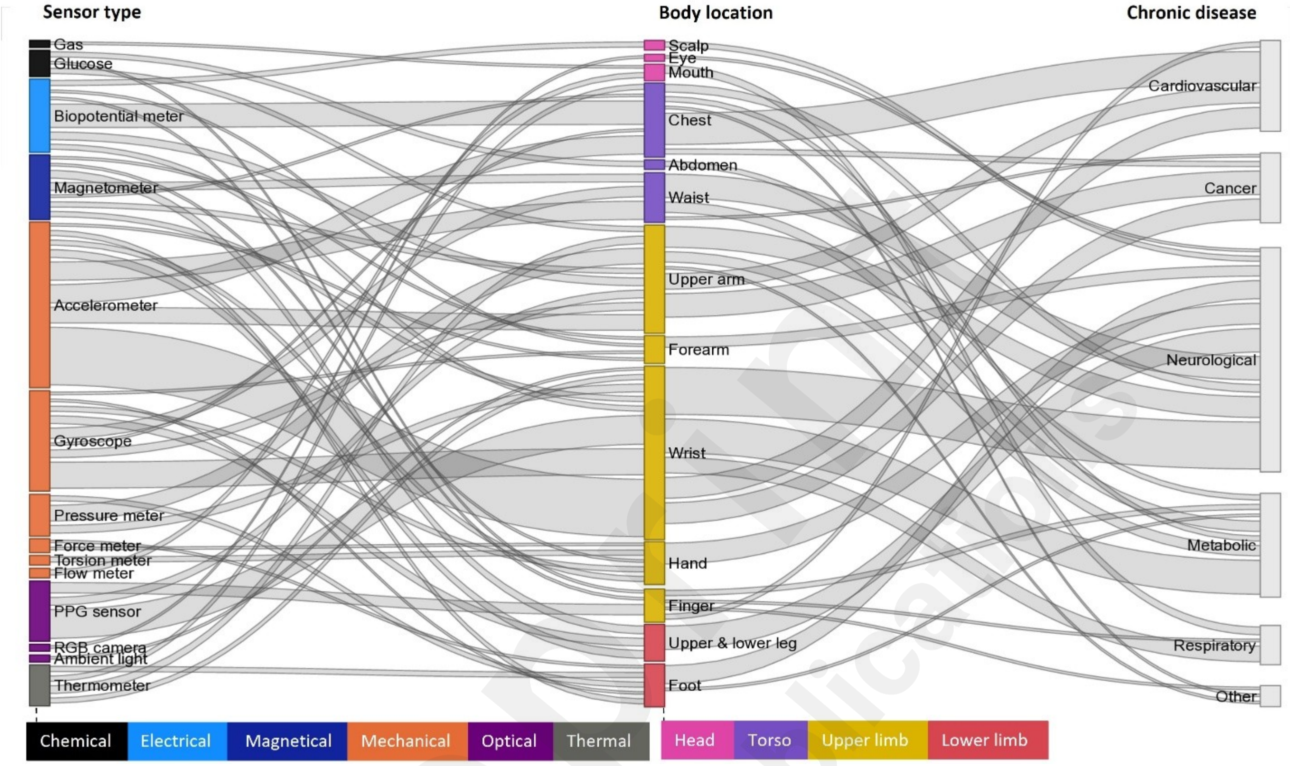

Figure 7. Body location for sensor types. Node and link width reflect the match frequency, and the node colors correspond to the sensor type and body location groups.

Medical application

The articles primarily highlight the use of wearable devices for monitoring specific chronic diseases as their main medical application, with the option to include wellness and lifestyle monitoring. Among chronic diseases, neurological diseases appear as the main focus, representing more than one-third (21 out of 61) of the articles. Cardiovascular diseases follow, with 15 articles, while wearable devices monitor cancer, metabolic diseases, and respiratory diseases in 11, 10, and 3 articles, respectively (Figure 8).

Furthermore, more than half (39 out of 61) of the articles target wellness and lifestyle applications alongside disease-specific metrics. Activity tracking is the fundamental wellness and lifestyle monitoring collected in 39 articles. Notably, activity remains essential for monitoring neurological diseases. Furthermore, sleep monitoring is another application widely tracked for various chronic conditions in ten articles. For cancer, neurological, and metabolic diseases, the articles describe remote stress-level monitoring (Figure 8).

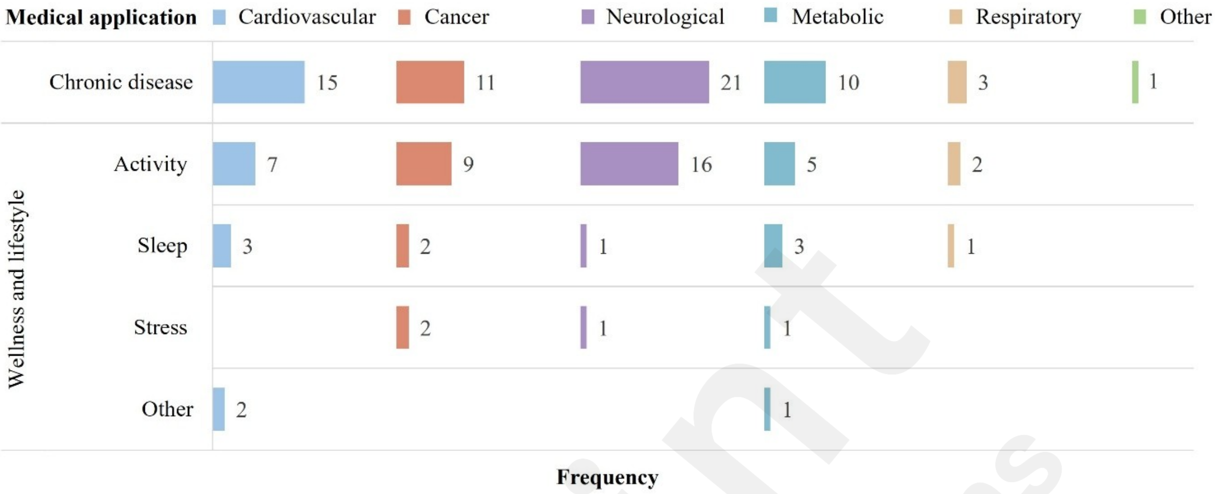

Figure 8. Frequency of medical applications in 61 articles on chronic disease monitoring. Among them, 39 include wellness and lifestyle applications. Rows represent the number of articles, columns the chronic disease, which may exceed the total article count because articles report on multiple wellness and lifestyle applications.

Discussion

Principal findings and interpretation

We identify wearable devices, sensor types, health parameters, body locations, and medical applications for remote monitoring of chronic diseases. Bands are the most popular wearable devices, integrating eight sensor types to monitor chronic diseases (Figure 3). Bands gain popularity because of advancements in RPM platforms, including Fitbit (34,50,61,65,81), Apple (61,67,69,84), Garmin (62,91), Huawei (63,71), Samsung (84), Withings (68), Omron HeartGuide (66), and Misfit (82). These brands offer diverse wearable devices, including smartwatches, wristbands, armbands, and straps.

Wearable devices commonly integrate accelerometers, and movement detected with accelerometers is an important health parameter for remote monitoring of chronic diseases. It provides valuable insights to set activity plans that promote wellness and prevent disease progression. Specifically, by tracking acceleration, researchers can gain a deeper understanding of movement patterns, which serve as key indicators of Parkinson's disease (98–100), while also assessing motor function and recovery following a stroke (101,102). Acceleration is also a key health parameter for monitoring physical fitness levels and evaluating treatment effectiveness in cancer patients (103). Additionally, PPG sensors, biopotential meters, pressure meters, and thermometers frequently monitor core and extended vital signs. Monitoring vital signs is crucial for managing chronic diseases, as it offers critical information about a person's overall health (104). Hence, vital signs play a pivotal role in chronic disease management, serving as early indicators for detecting and preventing patient deterioration (105).

The wrist is the most-frequent body location for sensor placement, as technological advancements make the wrist a convenient and popular location for monitoring physiological parameters (106). Innovations in smartwatches, wristbands, and bracelets integrate various sensor types, such as accelerometers and PPG sensors, making wrist-based monitoring particularly effective (107,108). In addition to the wrist, the upper arm and the chest are optimal locations for multiple sensor types. To monitor ECG, the chest frequently holds biopotential meters; as Stracina et al. consider it as gold standard for monitoring heart activity (109). Affected by skin type and hair density, PPG sensors are less accurate when worn on the chest (110–113).

The extremities hold IMUs to monitor neurological diseases (114–116), which is the leading medical application of wearable devices for remote monitoring of chronic diseases, followed by cardiovascular diseases. In 2024, the report from the Institute for Health Metrics and Evaluation (IHME) in the USA supports this finding, noting that "neurological diseases recently emerge as the leading global cause of disease burden and disability, affecting 43% of the global population (3.4 billion people)" (117,118). Neurological diseases account for 443 million years of healthy life lost, surpassing the impact of cardiovascular diseases. These diseases link to quantifiable biomarkers, such as gait analysis, tremors, speech patterns, and cognitive functions, which make wearable-based RPM systems highly effective. Wearable devices, such as bands, effectively capture and analyze these biomarkers, offering early prediction and prevention. Furthermore, wearable devices monitor cardiovascular diseases, which are the leading cause of death globally (119).

Wellness and lifestyle monitoring are other applications for remote chronic disease management. Approximately two-thirds of the articles track physical activities, such as count steps and determine movement. Additionally, movement-related parameters like tremors, motor symptom assessment, and muscle vibration are essential for diagnosing neurological diseases. Our findings align with the WHO report indicating that promoting healthy behaviors or responding to warning signs prevents 80% of chronic diseases (120). Furthermore, our results align with previous research showing that regular physical activity is crucial for managing chronic diseases (121,122), preventing new diseases (123–125), reducing medication needs (126,127), and improving quality of life (128–131). Hence, we emphasize the importance of setting physical activity plans as a strategy to prevent the progression of chronic diseases.

Moreover, remote sleep monitoring emerges as another wellness and lifestyle monitoring, as reflected in 10 articles. Evidence from the CDC (132) and the Population Reference Bureau (133) in the USA supports these findings, highlighting that various chronic diseases, including cardiovascular and metabolic, are linked to poor sleep. As a result, we underscore the importance of monitoring and addressing sleep problems to prevent health deterioration and promote healthy behaviors in chronic patients.

Strengths and limitation

Our analyses are unique in their approach, as they comprehensively identify wearable devices, sensor types, health parameters, body locations, and medical applications according to standardized terminology. This strategy offers valuable insights for designing wearable devices for comprehensive RPM systems and establishes a baseline for further studies on wearable devices. Using standardized terminology reduces healthcare costs by minimizing the monitoring systems, particularly those that capture the same data.

However, limitations arise from excluding articles that do not implement RPM systems and those that focus on unobtrusive or implantable sensors. Nonetheless, this exclusion enhances the accuracy of the results and improves generalizability, especially regarding the medical application of wearable devices for remote monitoring of chronic diseases. Moreover, this review primarily analyzes the frequencies of occurrence, which are not necessarily the most effective options. Hence, we recommend future research assessing the quality of sensor types across various chronic diseases and body locations.

Conclusion

- Bands are the most popular wearable devices for remote monitoring of chronic diseases.
- The most frequent sensor types are accelerometers, PPG sensors, biopotential meters, pressure meters, and thermometers.
- The most widely collected health parameters are acceleration, heart rate, body temperature, blood pressure, and SpO_2.
- The wrist is the preferred body location, followed by the upper arm and the chest.
- Medical applications are primarily the monitoring of neurological and cardiovascular diseases.
- Monitoring activity and sleep quality are other key applications of wearable devices.

Declaration

Author contributions: MDT and TMD conceptualized the study and designed the terminology. MDT and VS handled the study selection. All authors discussed and approved the extracted data. MDT designed the original draft. TMD, PH, VS, SRNK, and JW reviewed and edited the manuscript. MDT and TMD worked on the visualizations and finalized the manuscript. TMD supervised the study. All authors read and approved the final version of the manuscript.

Funding: This research received no external funding.

Institutional review board statement: Not applicable.

Informed consent statement: Not applicable.

Data availability statement: Not applicable.

Conflicts of interest: The authors declare no conflict of interest.

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Supplementary Files

Multimedia Appendixes

PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) checklist.
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Search strings.
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