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Visual analysis of research trends and hotspots in wearable electronic devices in the medical field: A bibliometric study

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Abstract

Background: Healthcare services and functionalities need comprehensive upgrades, and advancements in information technology have driven research in wearable electronic devices (WDs), making them critical tools for this purpose.

Objective: To conduct a systematic bibliometric analysis of WDs in the medical field and understand research trends.

Methods: A literature search of articles related to WDs in the medical field was conducted in the Web of Science Core Collection (WoSCC) from 2013 to 2023. Articles were analyzed using CiteSpace 6.1.R6.

Results: Publications on WDs have increased yearly since 2014, peaking in 2021. The United States leads with 935 articles. PLOS One is the top journal, and Bland et al. have the highest citation frequencies. Hot topics include mobile apps, phones, and neural networks, with research on physical activity, sleep monitoring, and atrial fibrillation.

Conclusions: This study identifies key journals, countries, institutions, and authors in WDs research, highlighting trends and global interest in health monitoring and assessment. The United States leads in research, with future trends focusing on neural network monitoring, accuracy improvements, cloud storage, and advancements in healthcare management systems.

Keywords

Wearable electronic devices, medical care, health management, research hotspots, development trends

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The field of healthcare is currently undergoing an unprecedented convergence, and characterized by the fusion of wearable technology with medical and healthcare applications. Terminal devices, represented by wearable electronic devices (WDs), are rapidly diversifying and increasing in number. Simultaneously, they are rapidly evolving towards networked, open, portable, intelligent, and wearable directions. Emerging information products and technologies, especially smart wearable devices, are driving a comprehensive upgrade of services and functionalities in the healthcare sector. Healthcare is considered the most promising application area for smart wearable devices, and it is expected to bring innovation and transformation to the healthcare industry.

The concept of wearable technology can be traced back to Professor Edward,[1] which immediately drew the attention of scholars worldwide. As wearable technology undergoes continuous updates and iterations, it has evolved from its initial stage as electronic textiles or smart textiles[2] to include torso-worn devices,[3] lower limb-

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worn devices,[4] head-mounted wearable devices,[5] wristband-type wearable devices,[6] and wearable patches.[7] WDs, in the form of portable medical or health electronic devices, can be directly worn on the body. Leveraging various technological means such as identification, sensing, connectivity, cloud services, and storage, they enable comprehensive functions for health perception, recording, analysis, regulation, and intervention. They play a pivotal role in preventive monitoring of early disease symptoms, ultimately achieving the goal of health management. With the continuous maturation of technologies such as big data, the internet, semiconductors, and sensors,[8] providing personalized healthcare, support, and information to individuals should be facilitated through wearable interfaces that are user-friendly. This approach brings technological advancements closer to the user,[2] making WDs critical tools for realizing this objective. The introduction of wearable technology opens up new possibilities for personalized healthcare, with WDs poised to become essential applications in the realms of future displays, robotics, in vitro diagnostics, advanced therapies, and energy harvesting.[9]

WDs have become a significant part of the lifestyle and fitness markets, and the development of wearable sensors in the healthcare market has progressed relatively slowly.[10] Although previous research has explored the applications of WDs in the healthcare sector, these studies have often lacked intuitive discussions and perspectives. Therefore, this study conducts a visual and systematic analysis of the research hotspots and development trends of WDs in the healthcare domain. It delves into the hotspots of WDs from multiple dimensions and suggests directions for future research. The analysis seeks to identify key research trends, including leading journals, countries, institutions, and authors contributing to the literature. This study aims to perform a systematic analysis of WDs in the medical field from 2013 to 2023, utilizing visualizations such as icons and graphs to present the development hotspots and trends of WDs, providing clear and concise information to stakeholders including medical researchers, policymakers, and interdisciplinary scholars. This approach enhances the comprehensibility of the research findings. This study highlights the global interest in health monitoring and assessment through WDs and outlines future research directions, with a particular focus on advancements in neural network monitoring, accuracy enhancements, cloud storage solutions, and improvements in healthcare management systems.

Materials and methods

Data source collection

We chose the Web of Science Core Collection (WoSCC) database for this study. Specifically, we request that the literature source be limited to the WoSCC core collection and that the citation index be limited to SCIE. Wearable electronic gadgets, WDs, wearable equipment, wearable medical instruments, and wearable health equipment were the search phrases used. Textbox 1 lists the inclusion and exclusion criteria for literature selection. The flowchart (Figure 1) provides comprehensive search processes. 2319 literature records in all were found. These entries contained basic document attributes such as author names, titles, abstracts, source publications, keywords, nations, and references referenced and were exported in text-text format.

Textbox 1. Inclusion and exclusion criteria applied to select the references.

Inclusion Criteria:

1. Subject terms or keywords = Wearable Electronic Devices OR wearable device OR wearable devices OR wearable equipment OR wearable medical instrument OR wearable health equipment
2. Publication time range: 2013/01/01 to 2023/07/05
3. Document Typed: Article
4. Language: English
5. Categories: Medical

Exclusion Criteria:

1. Subject terms or keywords: Articles that do not include any of the following keywords: Wearable Electronic Devices, wearable device, wearable devices, wearable equipment, wearable medical instrument, or wearable health equipment.
2. Publication time range: Articles published before January 1, 2013, or after July 5, 2023.
3. Document types: Non-article formats such as editorials, reviews, letters, or book chapters.
4. Language: Articles published in languages other than English.
5. Categories: Articles not categorized under Medical or related fields, including those focused on non-medical applications of wearable devices.

Data visualization and analysis

In order to investigate the research hotspots and trends of WDs in the field of clinical medicine, this study conducted a series of bibliometric analyses of relevant literature. Bibliometrics is a process that involves quantitative analysis of a large volume of scientific literature using various types of literature analysis software programs for visualization and presentation of results. It allows for the measurement of research trends and knowledge structures in a particular field, resulting in quantitative and objective data.[11] In this paper, all data from the WoSCC database were processed using the following functions of

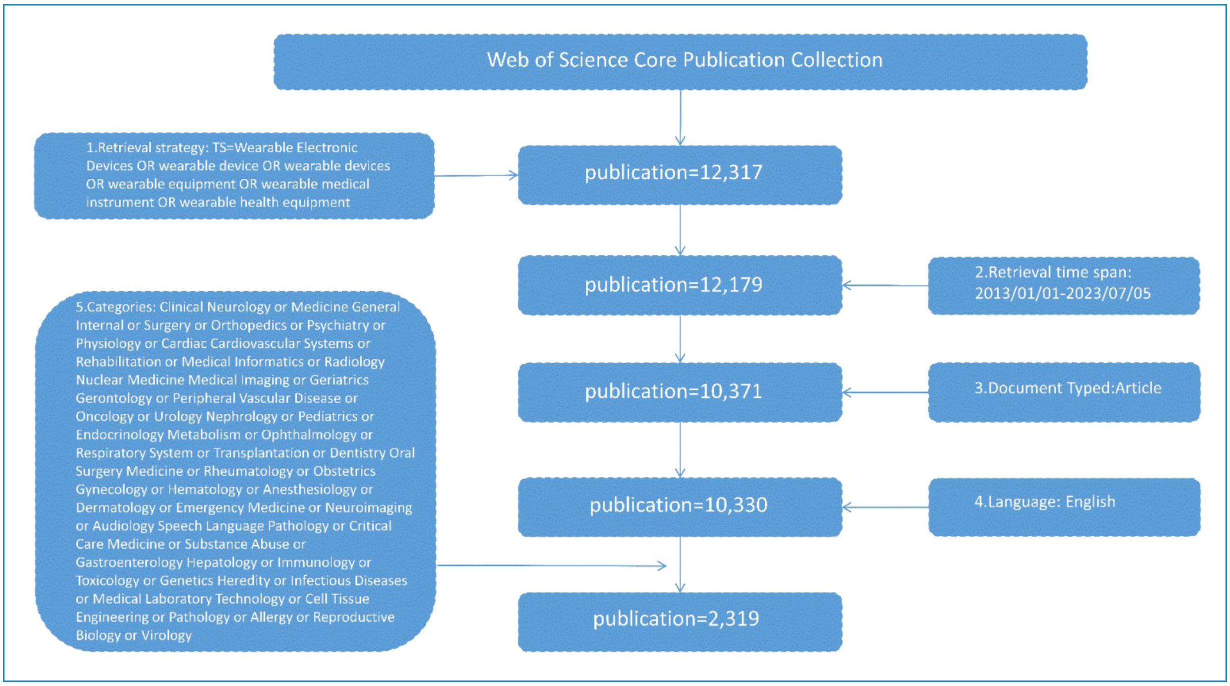

Figure 1. Flowchart of literature selection.

CiteSpace software (version 6.1 R6; Drexel University): conversion into the Web of Science pure format and removal of duplicates through the dol. list file of citing articles.[12] CiteSpace analysis was employed to illustrate the development trends and research hotspots of WDs in the clinical medicine field, as well as to predict their evolutionary path and research frontiers. After processing, a total of 2318 literature records were included, forming a database subsequently used for visual analysis.

The following settings were made to the CiteSpace software: (a) time frame (2013–2023), with each slice denoting a single year; (b) because there was a substantial amount of literature to be analyzed, we used several network pruning techniques for various analysis objects. With a g-index of 5 and a Top N of 50, we chose Pathfinder, Pruning Sliced Networks, and Pruning the Merged Network for cited journals. G-index = 5 was used to configure the keyword time zone map without performing any network pruning. We selected Pathfinder and Pruning as the combined network for the institution analysis. No network pruning was used for author analysis, and author co-citation was set to 10 with a g-index of 10. The pruning settings were Pathfinder, Pruning sliced networks, and Pruning the merged network. Additionally, all other settings for other analysis objects were left at their default settings; (c) to examine the development patterns and research hotspots in the field of WDs in medicine, we used "K" and log-likelihood rate (LLR) for cluster analysis. Cluster graph quality was assessed using Modularity Q and Mean Silhouette. Typically, clustering is regarded as significant and practical when $Q > 0.3$ and $S > 0.5$. Additionally, if $S > 0.7$, the grouping may have great persuasive power. We created dynamic visual knowledge maps and publication volume patterns over time to provide a more understandable picture of the changes in the medical field of WDs. We may learn more about the research hotspots and development trends in the sector from these graphs.[13,14]

Results

Visualization of publication numbers

The annual variations in the number of published articles directly illustrate the distribution of research paper quantities in the field of WDs. Based on our search results, we conducted a comprehensive analysis of global publication trends and created a line graph depicting the included literature. Figure 2 illustrates the temporal distribution of research literature publications in the clinical medical field of WDs. From 2013 to 2021, the number of publications steadily increased with a noticeable overall upward trend. Before 2014, there were relatively few studies related to WDs. However, starting in 2015, there was a sharp increase in the number of relevant articles, indicating widespread interest in research on WDs in the medical field. From 2021 onwards, the number of literature publications has remained relatively stable. The number of publications in 2023 has declined compared to the previous 5 years. Given the cutoff date of our literature search, we are currently unable to determine whether the total number of

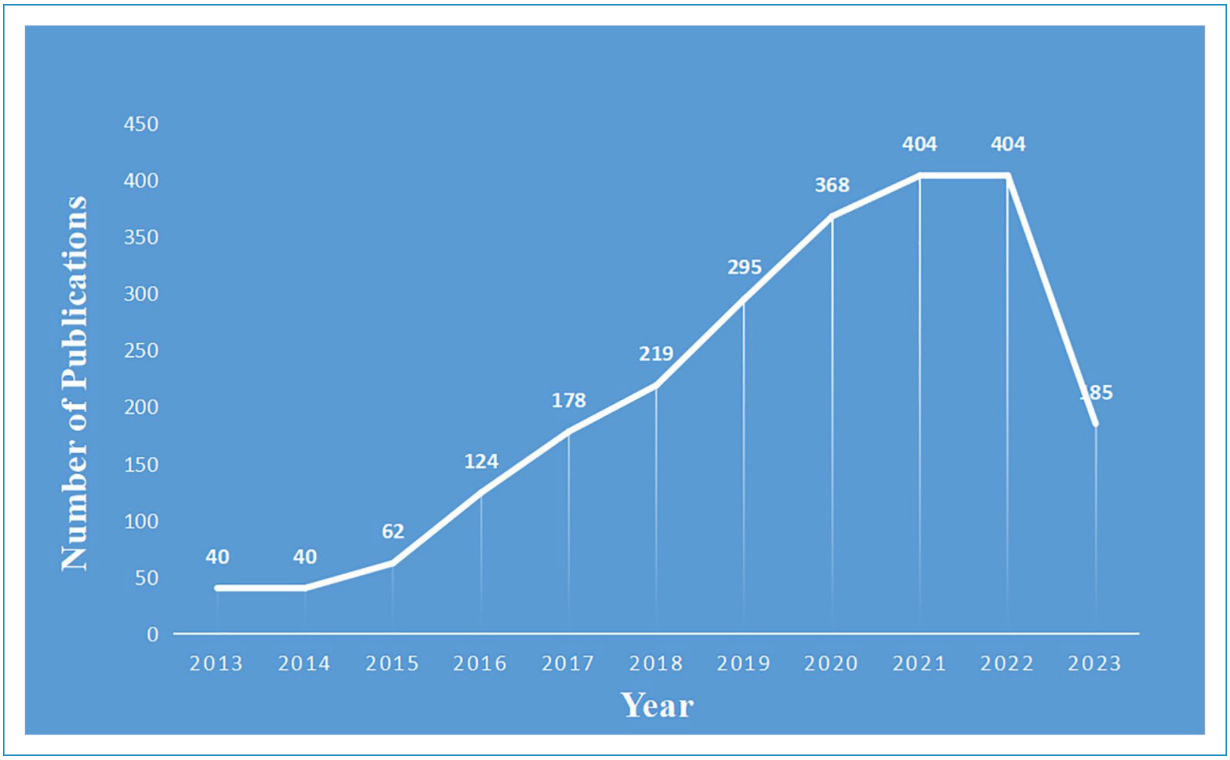

Figure 2. Temporal distribution of research publications on wearable devices in the medical field.

Table 1. The top 10 countries/regions in number of publications.

Rank	Countries/ regions	Total publications	% of 2319	Rank
1	USA	925	39.888	1
2	UK	268	11.557	2
3	CHINA	219	9.444	3
4	ITALY	180	7.762	4
5	AUSTRALIA	163	7.029	5
6	GERMANY	148	6.382	6
7	SOUTH KOREA	135	5.821	7
8	CANADA	126	5.433	8
9	NETHERLANDS	123	5.304	9
10	SWITZERLAND	110	4.743	10

publications in 2023 will surpass or continue to decline from previous years.

The article with the highest citation rate from 2013 to 2023 was published in 2017 and has been cited as many as 872 times. This study reviewed the applications of deep learning in health informatics, analyzing its advantages, limitations, and future prospects. It focused on applications in bioinformatics, medical imaging, sensing, informatics, and public health.[15] Additionally, we also took note of the second most-cited article, published in 2019 by the New England Journal of Medicine, which reported a large-scale study on the use of intelligent WDs for monitoring atrial fibrillation (AF) in populations.[6] The article explored the ability of optical sensors on WDs to detect irregular pulses and whether smartwatch applications could identify AF in typical use. Participants without AF used the application for monitoring, and if irregular pulse notifications suggested possible AF, they were provided with remote medical access and electrocardiogram (ECG) patches. Among the participants, 0.52% received irregular pulse notifications, and 34% of volunteers reported AF in subsequent ECG patch readings. The evaluation results of this study laid the foundation for subsequent large-scale practical research on smart devices.

Visualization of cooperating countries/regions and institutions

Table 1 reveals the top three most prolific countries: the United States ($n = 925$, accounting for 39.888% of the total); the United Kingdom ($n = 268$, accounting for

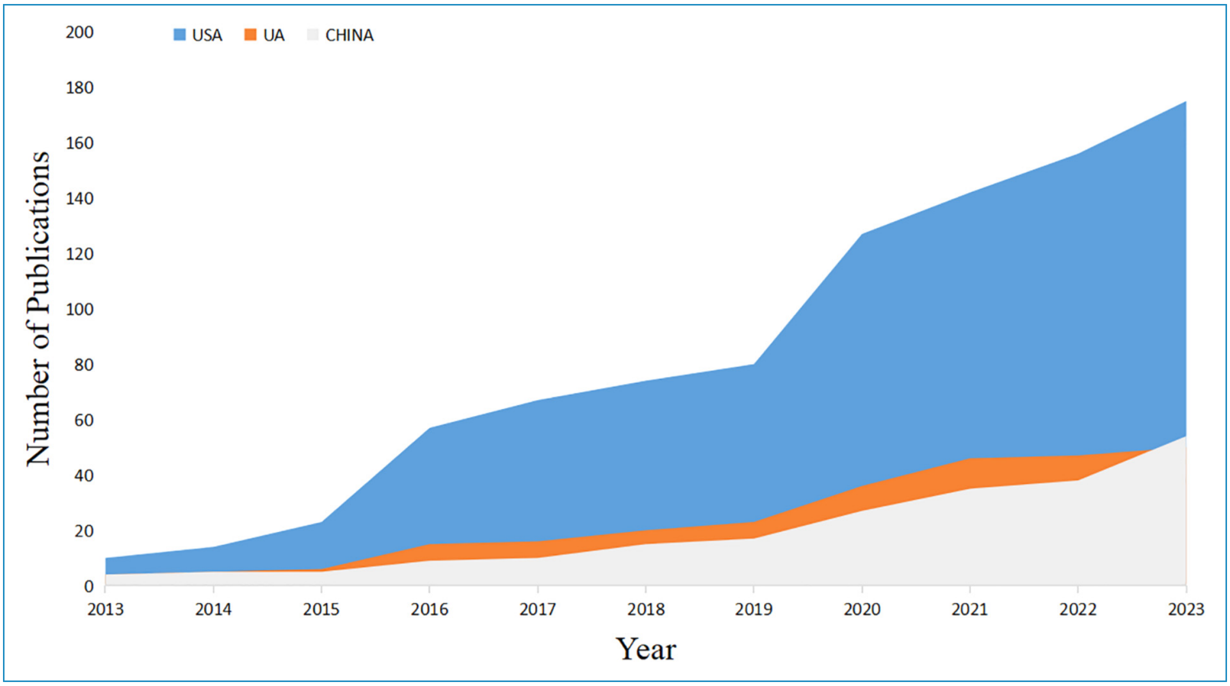

Figure 3. The annual publications of the top 3 countries from 2013 to 2023.

Table 2. The top 10 institution in number of publications.

Rank	Institution	Country/territory	Publications	Centrality
1	Harvard Med Sch	USA	63	0.08
2	Northwestern Univ	USA	53	0.02
3	Univ Michigan	USA	43	0.06
4	Kings Coll London	UK	43	0.17
5	Duke Univ	USA	42	0.35
6	Stanford Univ	USA	40	0.02
7	Univ Toronto	CANADA	34	0.04
8	Univ Washington	USA	30	0.13
9	Univ Calif San Francisco	USA	30	0.15
10	Emory Univ	USA	29	0.03

11.557%); and China ($n = 219$, accounting for 9.444%). Figure 3 summarizes the annual publications of these three countries from 2013 to 2023, intuitively reflecting that among the top three ranked countries, the United States leads the world by a significant margin in terms of publication volume, while the gap between the second-ranked United Kingdom and the third-ranked China is not substantial. In the top 10 most productive countries, the United States boasts the highest H-index of 72, surpassing other countries/regions by a considerable margin. Furthermore, we analyzed the countries' rankings based on the average citation per paper, with the United

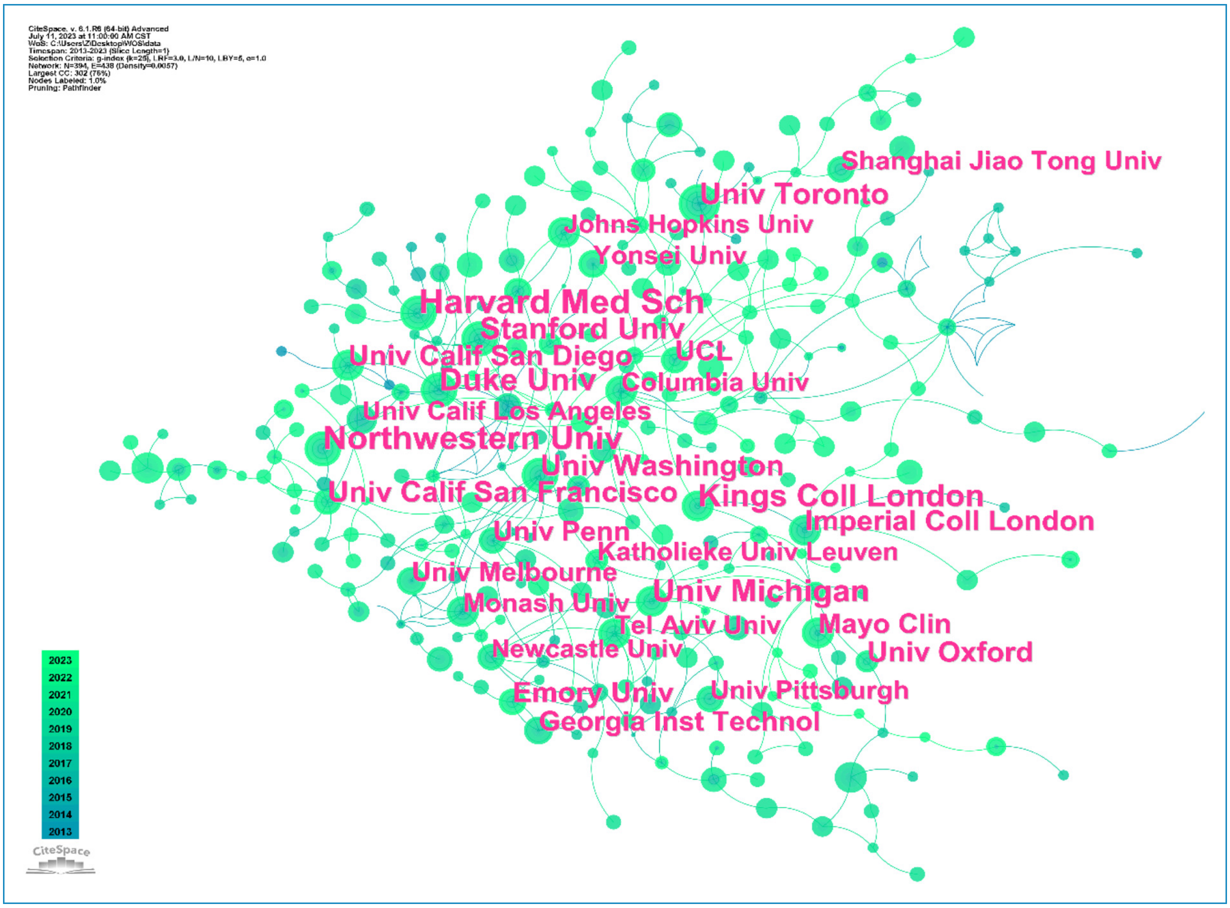

Figure 4. Collaborative network diagram of different institutions.

States (22), the United Kingdom (21.55), and China (16.66) occupying the top positions.

Based on the analysis of institution node size and publication output, 9 out of the top 10 research institutions are located in the United States (Table 2). The institution with the highest number of published articles is Harvard Medical School (63), followed by Northwestern University (53), University of Michigan (43), and King's College London (43). Other institutions with more than 29 papers will also continue to make outstanding contributions to the field of wearable intelligent devices in medicine. These include Duke University (42), Stanford University (40), University of Toronto (34), University of Washington (30), University of California, San Francisco (30), and Emory University (29). Additionally, noteworthy are the burst values of the University of California, Los Angeles (4.66), University of British Columbia (4.42), and Harvard University (4.03), all exceeding 4. This indicates that these universities possess strong momentum in this field in the short term.

As depicted in Figure 4, leading research institutions consist of 393 publication entities, with collaborations among key universities primarily concentrated within the United States. Notable connections include Stanford University with Duke University and Northwestern University with the University of California, Los Angeles. We observed a nationwide cross-sectional survey conducted by Harvard Medical School,[16] which revealed that a high 9.6% of the population had experienced tinnitus in the past 12 months. However, only a mere 2.6% of them opted for wearable masking devices among various treatment measures.

Visualization of main journals

In this study, the CiteSpace system was used to generate a map of cited journals for node 236 and row 610 (Figure S1). Table 3 lists the basic information of the top 10 journals with a total number of citations for WDs in the medical field, respectively. It is worth noting that the top three impact journals all belong to Journal Citation Reports 2022 (JCR) Region 2, which are PLOS One (771), followed by Sensors (557) and IEEE Transactions on Biomedical Engineering (476), which indicates that articles published in these publications make significant contributions to WDs and reflects the relative quality of publications in

Table 3. Top 10 journals in terms of WDs.

Rank	Publication journal	Count	JIF 2022	JCR quartile 2022
1	PLOS One	771	3.7	Q2
2	Sensors	557	3.9	Q2
3	IEEE Transactions on Biomedical Engineering	476	4.6	Q2
4	Lancet	464	168.9	Q1
5	JMIR mHealth and uHealth	452	5	Q1
6	Journal of Medical Internet Research	449	7.4	Q1
7	Journal of the American Medical Association	447	120.7	Q1
8	IEEE Engineering in Medicine and Biology Society	424		
9	New England Journal of Medicine	397	158.5	Q1
10	Circulation	397	37.8	Q1

Table 4. The top 10 co-authors in number of publications.

Rank	Authors	Count	Centrality
1	Bland JM	102	0.03
2	De Zambotti M	86	0.27
3	Tudor-Locke C	76	0.01
4	World Health Organization	71	0.09
5	Evenson KR	67	0.09
6	Camm AJ	62	0.06
7	Patel S	58	0.31
8	Patel MS	49	0.03
9	Allen J	48	0.16
10	Case MA	48	0.03

these journals. On the other hand, the IEEE Engineering in Medicine and Biology Society (424 citations) is a specialized organization and society focused on applying engineering principles and technology to the fields of medicine and biology. It is a significant academic organization in the fields of medicine and biomedical engineering that promotes scientific research and technological innovation. It achieves this by organizing academic events, publishing scholarly journals, and establishing a global network to facilitate academic exchange and collaboration, ultimately aiming to enhance human health and quality of life. The remaining journals are all in JCR region 1, with LANCET (IF = 168.9) having the highest impact factor, followed closely by The New England Journal of Medicine (IF = 158.5) and Journal of the American Medical Association (IF = 120.7) which suggests that these three journals may be the definitive publications on the medical aspects of wearable smart devices. Of particular interest is the journal with the highest centrality: Medicine and Science in Sports and Exercise (Centrality = 1.01, IF = 4.1). This journal is among the top journals in the field of exercise science, which has a strong focus on the use of WDs for monitoring exercise science, whose research often provides guidance on exercise prescription, injury prevention strategies, and rehabilitation programs that benefit athletes, patients, and individuals seeking to improve their physical fitness, and which plays a key role in disseminating the latest advances in exercise science and sports medicine to reach a global audience.

Analysis of authors and co-cited authors

The network density graph visualizing co-authorship relationships among authors is shown in Figure S2. It is evident from all the nodes that authors form several author clusters ranging in size from approximately 7 to 20 individuals. For example, there is a closely collaborating network centered around authors like Hotopf Matthew and Matcham Faith. This largest author group is connected to the author group of Wykes Til and Richardson Mark P. Node size in the graph directly indicates authors who have published a relatively large number of papers in the field of wearable medical devices, including Beniczky Sandor (16 papers), Inan Omer T (15 papers), and Dobson Richard J B (14 papers). Upon a detailed analysis of the publications by these three authors, it was found that Beniczky primarily specializes in epilepsy treatment. In 2019, his research team conducted forward-looking tests using wearable electromyography devices to automatically monitor generalized tonic-clonic seizures in patients with generalized tonic-clonic seizures, demonstrating the high sensitivity of wearable electromyography devices for generalized tonic-clonic seizures (sensitivity = 93.8%). This study has garnered widespread attention among scholars.[17] Inan's primary expertise lies in cardiovascular disease research, and he has consistently worked on improving cardiovascular health through wearable device technology.[18–20] Lastly, Dobson is an expert in researching and treating psychiatric disorders such as depression. He and his team[21] conducted research using wearable and mobile devices to capture sleep data in schizophrenia patients. The study demonstrated that schizophrenia patients exhibited high compliance with long-term use of mobile WDs and had positive implications for predicting clinical status, objective markers, and early relapse.

As shown in Table 4, among the top ten ranked authors in terms of the number of co-citations, Bland JM has the highest number of co-citations, followed by De Zambotti M and Tudor-Locke C, which shows their outstanding contribution to this academic field. However, according to Figure S3, only De Zambotti M, Patel S, and Allen J have centrality greater than 0.1 and are marked with a purple outer ring in the top ten authors' co-citation counts, which indicates that these three scholars have strong academic influence in this field.

Co-occurring keywords analysis

By accurately reflecting research hotspots and frontier themes in the professional area, the development of keywords in each cluster helps professionals and scholars comprehend the progress of the research field and, as a result, supports further research.[22] Each node represents a keyword, and the size of the node can be used to calculate the frequency of keyword occurrence and assess the significance of each keyword. A keyword co-occurrence graph with 485 nodes and 1784 linkages was produced after manually combining phrases with the same meaning (Figure 5). We discovered phrases strongly related to WDs, such as dependability, management, and intervention, among nodes denoted with purple circles, which signify high BC. Figure 6 displays the top 16 keywords with the strongest bursts, with red lines representing the duration of keyword bursts and blue lines representing the time intervals of each keyword burst. Among the top 5 keywords are: system, body sensor network, sensor, fatigue, and exoskeleton. Table 5 lists the top 10 keywords with the highest frequency and centrality in WDs. Keywords such as reliability, older adult, intervention, and recovery have both high frequency and centrality. In addition, keywords with high centrality include big data (0.26), activity recognition (0.22), and depression (0.2). It's also noteworthy that the keywords neural network, mobile app, and mobile phone indicate research directions that have received significant attention from scholars in recent years.

Analysis of thematic evolution

For keyword analysis, we conducted clustering using LLR analysis. The cluster names were determined based on the feature words within each cluster with the highest LLR values. The clustering results are shown in Figure 7. The modularity degree was 0.78, and the silhouette value was 0.91. In total, 18 clusters were generated.

We clustered keywords in the form of a timeline chart to facilitate understanding specific topics during certain periods and explore the knowledge structure and evolutionary trajectory in this field[13]. According to the data displayed in the keyword timeline chart (Figure 8), "polysomnography" is the largest category (#0), followed by "machine learning" (#1) and "physical activity" (#2), all of which have been active since 2013 to the present.

Discussion

Principal results

Through comprehensive visual analysis of WDs in the medical field, our primary findings are as follows: From 2015 to 2021, research on WDs has demonstrated a significant and robust growth trend. Through a co-citation analysis of journals, we identified the top 10 journals with the greatest impact on the WDs field, including "The New England Journal of Medicine," "The Lancet," and "Journal of the American Medical Association," among other high-quality journals. These journals have enjoyed widespread global dissemination and have played a crucial role in driving the development of WDs. Currently, the United States remains one of the most prominent nations in this field. According to publication counts from various institutions, the United States contributes to over half of the publications in the top 10 countries in the field of WDs research in the medical domain. On the other hand, in Asian countries, China holds a leading position, while European nations, such as the United Kingdom, Germany, and Italy, serve as key research focal points. Among the most active researchers, scholars like Beniczky Sandor, Inan Omer T, and Dobson Richard J B have made substantial contributions to the WDs field, and their research work has garnered significant attention.

In this study, we conducted a bibliometric analysis of medical research on WDs published in the past decade. This analysis has provided us with an in-depth understanding of emerging trends in this research field. The continuous advancement of WDs is playing an increasingly important role in global health promotion, and related research is receiving growing attention. These devices have found extensive applications in health monitoring and assessment, disease diagnosis and treatment, chronic disease management, and the rehabilitation process, contributing significantly to the progress of healthcare.[10]

By connecting these devices to patients' skin and storing the collected data in the cloud for easy monitoring by clinical professionals, this novel measurement approach facilitates the collection of large-scale case data. This is of

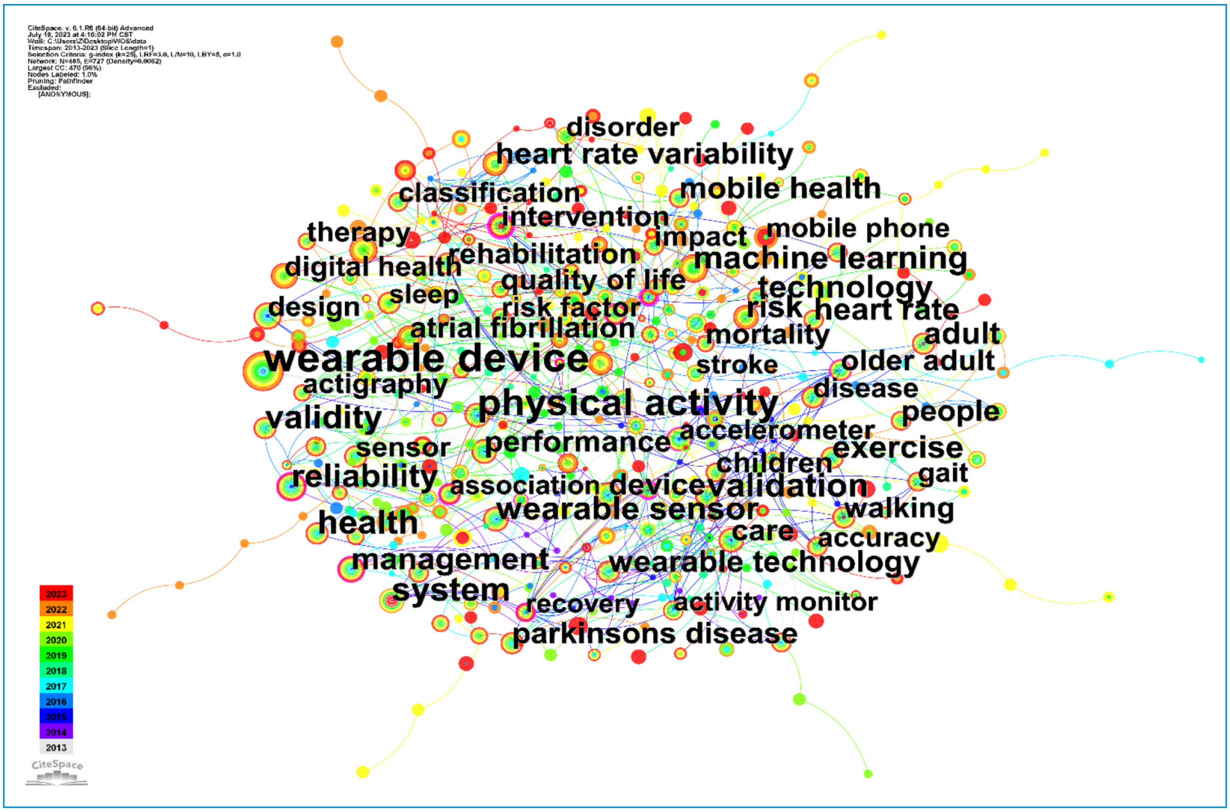

Figure 5. Visualization on co-occurring keywords network.

significant importance for the development of national epidemiology and preventive medicine strategies.[10]

Evolution and development of WDs in medicine

Based on the data shown in Figures 2 and 8 we divides the evolution of the field of WDs in medicine into three stages: emergence (before 2014), implementation (2015–2018), and development (started in 2018).

Emergence (before 2014)

In the initial stage of the development of wearable electronic device technology, many scientific studies emerged that were enlightening for today's medical biosensing, rehabilitation, and remote healthcare. In 1985, Rubow and Swift[23] pioneered research on the practicality of wearable biofeedback devices based on microcomputers for improving Parkinsonian speech disorders. Subsequently, through historical tracing, we found that early WDs relied on sensors, actuators, electronic components, and power sources based on electroactive polymers to form smart electronic textiles or e-textiles,[2] which can be considered as the precursor of today's WDs.

In order to enhance the quality of home healthcare, Axisa et al.[24] proposed the need to develop new types of WDs to improve patient comfort and safety. These devices should possess features such as intelligence, flexibility, and wearability and are expected to be integrated into mobile devices, smart clothing, or smart homes in the future. Building on previous research, wireless body sensor networks emerged to address the challenges posed by factors such as the ageing population, a significant increase in chronic disease prevalence, and limited healthcare resources.[25]

With the rapid advancement of Internet technology, smart homes, as part of home healthcare, gained attention. This technology requires sensors, actuators, and/or biomedical monitors to be connected to remote networks for collecting and processing data, which is used for remote central diagnosis. This data assessment helps determine whether a patient requires assistance. The carriers of this technology can be WDs or implantable devices.[26]

To drive the development of mobile health technology, Kumar et al.[27] innovatively introduced new mobile health information and sensing technologies, known as mHealth, which is represented by the theme "mobile health" (#9). This technology not only reduces healthcare costs but also improves overall health. Upon analysis and summary, we found that during this period, research directions were more focused on themes such as "wearable sensors" (#13) and "mobile health" (#9).

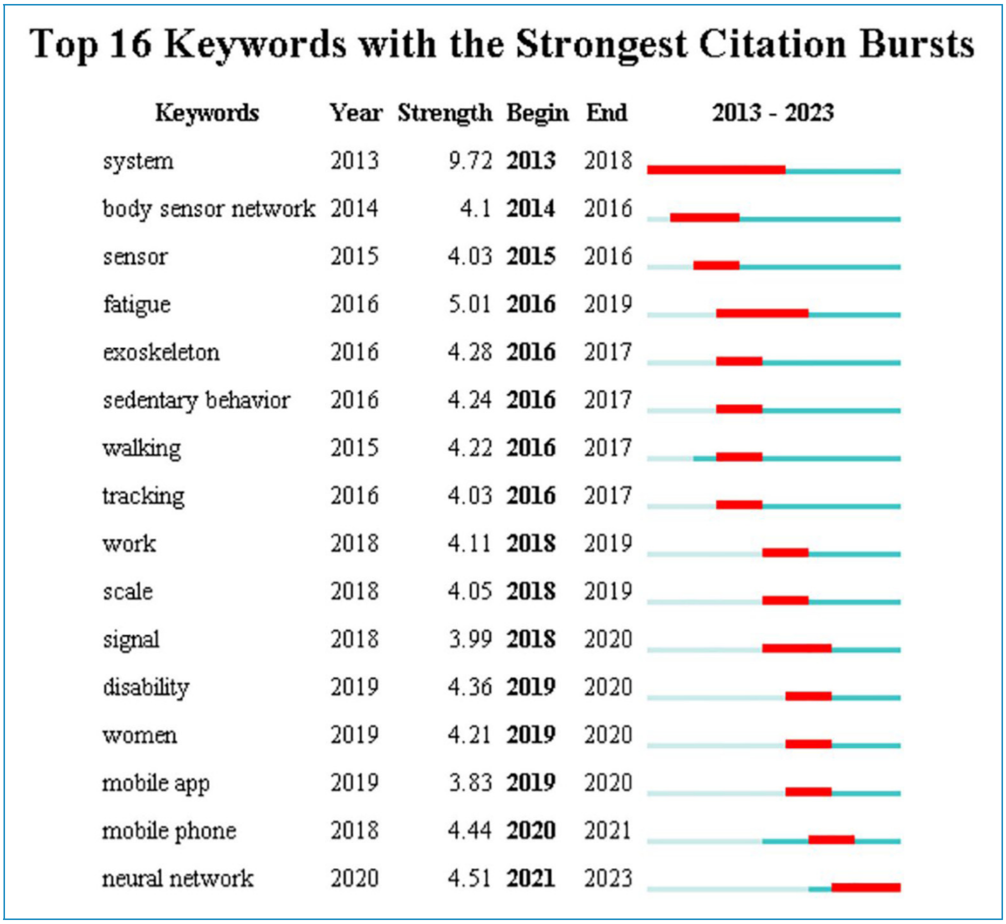

Figure 6. Top 16 keywords with the most strongest bursts.

Table 5. Top 10 keywords in terms of WDs.

Rank	Frequency	Centrality	Year	Keywords	Frequency	Centrality	Year	Keywords
1	451	0.05	2013	Wearable device	17	0.26	2015	Big data
2	275	0.03	2014	Physical activity	64	0.25	2015	Intervention
3	140	0.09	2013	System	20	0.22	2013	Activity recognition
4	139	0.01	2015	Health	39	0.20	2016	Depression
5	137	0	2015	Validation	73	0.19	2015	Older adult
6	126	0.07	2014	Validity	46	0.17	2015	Recovery
7	113	0.13	2013	Reliability	9	0.17	2019	Network
8	111	0.02	2014	Wearable sensor	3	0.16	2015	Wearable computing
9	111	0.02	2017	Machine learning	1	0.14	2014	Ambulatory children
10	103	0	2015	Technology	113	0.13	2013	Reliability

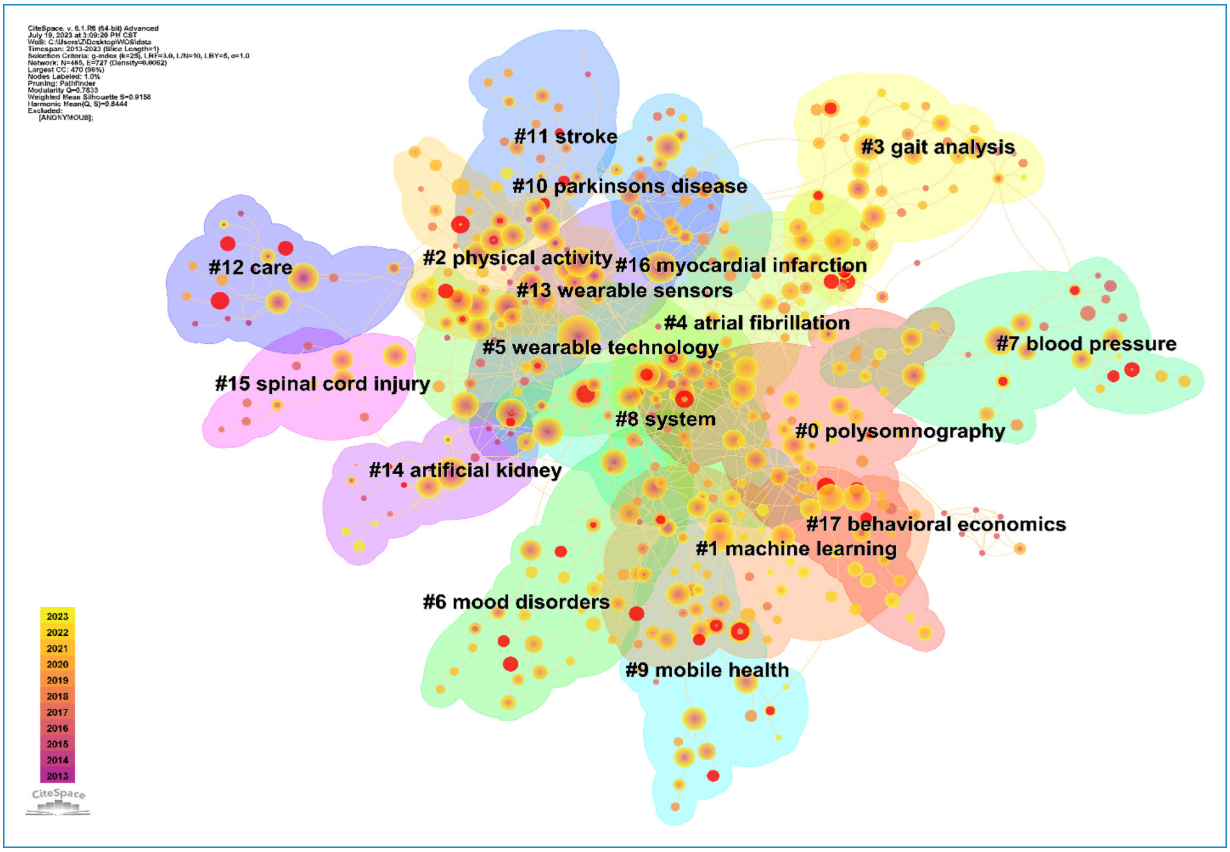

Figure 7. Cluster analysis of keywords network.

Implementation (started in 2015)

Against the backdrop of increasing healthcare costs, rising health issues, shortcomings in continuous health monitoring at both individual and population levels, and a lack of awareness in self-health management of chronic diseases, mHealth technology has continued to develop. It aims to reduce preventive health problems and decrease healthcare visits.[28–30] Consequently, researchers have begun to focus on specific areas, such as self-health management of chronic diseases.[31, 32]

Given the global attention to strategies for an ageing population, more emphasis has been placed on themes such as "polysomnography" (#0), "parkinsons disease" (#10), "gait analysis" (#3), and "physical activity" (#2). This includes emerging management approaches for Parkinson's disease,[33] mHealth technology interventions to promote physical activity,[34] and the assessment of the accuracy of WDs in sleep monitoring.[35] Gait is often closely associated with Parkinson's disease, so WDs are being used to capture early pathological gait results in the elderly, which can be used to identify early signs of neurodegenerative changes.[36]

It's worth noting that the theme of "machine learning" (#1) has gained academic attention during this period. Deep learning, as a subset of machine learning based on artificial neural networks, has been widely applied in fields like translational bioinformatics, medical imaging, pervasive sensing, medical informatics, and public health. Its emergence signifies a reshaping of the future of artificial intelligence.[15] For example, Ravi et al.[37] innovatively introduced a deep learning approach that integrates learned features from inertial sensor data with additional information from a series of shallow features. This approach is unique in achieving high accuracy and real-time activity classification. Themes that have received significant development during this period include "polysomnography" (#0), "parkinsons disease" (#10), "gait analysis" (#3), "physical activity" (#2), and "machine learning" (#1).

Development (started in 2018)

As wireless body sensor networks technology underwent iterative updates, Katsigiannis et al.[38] aimed to overcome the limitations of WDs in human emotion recognition. They established a multimodal database composed of electroencephalogram and ECG signals recorded during emotional stimulation through audiovisual stimuli. This database, captured using low-cost wireless WDs, aimed to

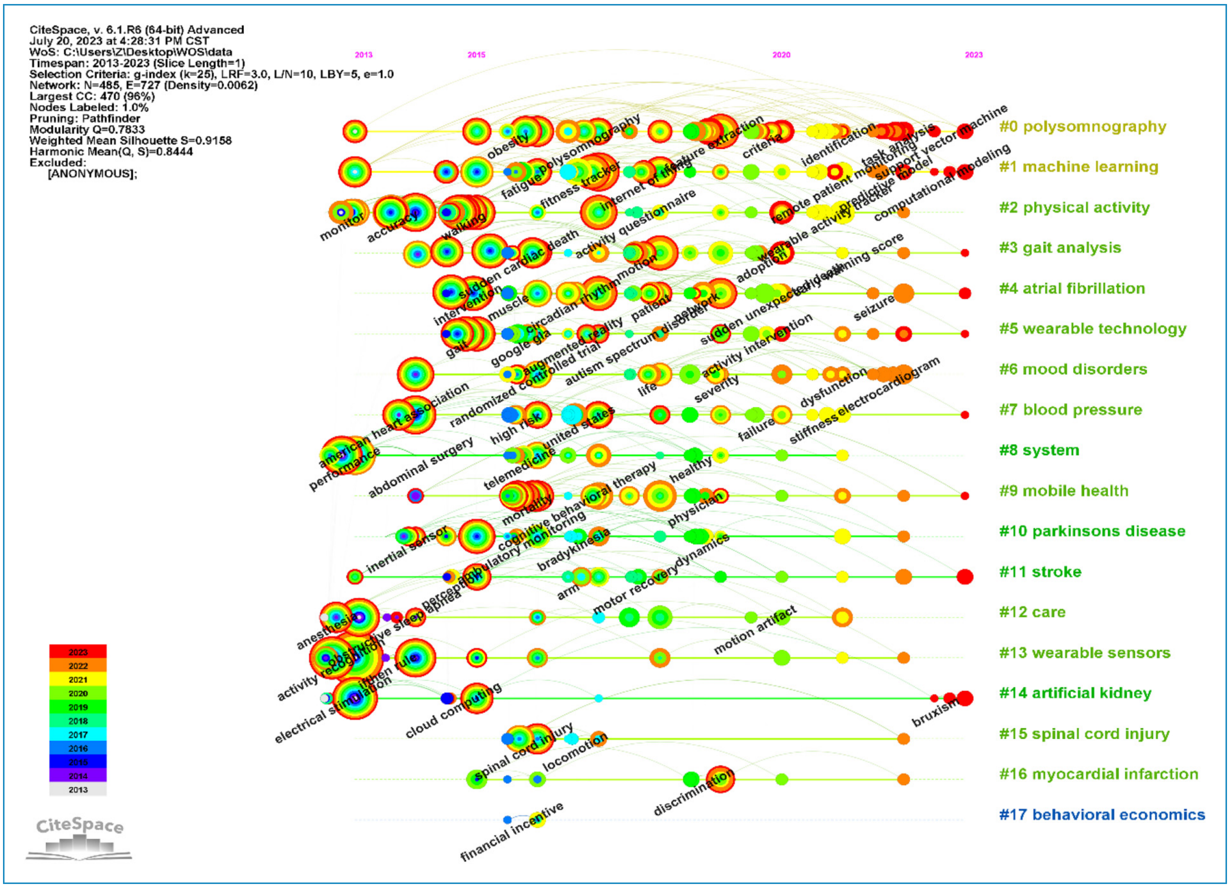

Figure 8. Keyword timeline visualization.

trigger specific emotions. AF is one of the most common persistent chronic arrhythmias in the elderly population. For daily monitoring of AF in the elderly, Fan et al.[39] developed a multiscaled fusion of deep convolutional neural network to effectively screen for AF (accuracy > 96%).

Notably, the theme of “myocardial infarction” (#16) regained significance during this period, thanks to a randomized controlled trial published in the New England Journal of Medicine in 2018.[40] The results of this paper demonstrated a significant reduction in mortality due to arrhythmias in the experimental group equipped with wearable defibrillators compared to the control group. This study marked a major advancement in the use of WDs for AF.

Subsequently, wearable device technology made breakthroughs. Turakhia,[41] Perez,[6] and Wasserlauf et al.[42] each focused their research efforts on the identification and screening of AF using wearable technology. Simultaneously, the accuracy of wearable technology garnered the attention of some researchers. For instance, Bent and their research team[43] conducted a comparative study analyzing heart rate and photoplethysmography data from consumer-grade and research-grade WDs in various scenarios. The results revealed higher accuracy for different WDs in resting and extended heart rate measurements, although some variations were observed in their response to changes in physical activity.

Upon tracing the timeline, it becomes evident that the themes of “polysomnography” (#0), “machine learning” (#1), “blood pressure” (#7), and “atrial fibrillation” (#4) are the current focal points of scholarly attention and represent ongoing research trends.

Future hotspots of WDs

Since 2013, there has been a rapid upward trend in the publication of research related to WDs in the medical field. WDs, by collecting user-relevant data and resources, assist users in better understanding and assessing their health information based on personal experiences. This, in turn, promotes further individual health management behaviors. Efficient healthcare terminals can provide comprehensive health education to enhance the electronic health literacy of the general public.[11]

The continuous advancement of new technologies, such as semiconductors, sensors, 5G technology, and big data, is driving the smart development of WDs. From keyword clustering analysis, keyword bursts, and topic evolution, research on WDs encompasses various subjects, including machine learning, mobile health, and wearable sensors, among others. Accuracy in the daily monitoring of different types of diseases using WDs such as polysomnography, AF, mood disorders, blood pressure, and stroke has been analyzed. Researchers have also developed various types of wearable tools to promote the advancement of WDs, as shown in (Table S1). These tools differ in terms of wearability and advantages.

Therefore, based on keyword co-occurrence networks, keyword timeline views, high-frequency keyword statistics, clustering, and thematic evolution paths, along with insights from classical literature content, we predict that mobile apps, mobile phones, and neural network may become research hotspots in the future of WDs.

In 2015, commercial radio-frequency identification chips successfully read biomarkers in sweat with an accuracy of up to 96% through an Android TM smartphone application.[44] In 2018, Apple developed a new technology called the Kardia Band, which allows patients to record rhythm strips using an Apple smartwatch. This wristband pairs with an application that can automatically detect AF.[45] In 2019, Apple conducted a large-scale prospective single-arm pragmatic trial, measuring the proportion of individuals with AF monitored by Apple Watch's dynamic ECG patch and the rate of first contact with healthcare providers within 3 months of pulse anomaly notification, all conducted electronically through the accompanying smartphone application. The study's findings provide insights into how wearable technology can support clinical approaches to identifying and screening for AF.[41] Devices like these and other innovative technologies mark the beginning of a new era in health monitoring, screening, assessment, and intervention. For the general public, the innovative integration of WDs and wireless technology fills the technological gap needed for real-time monitoring of human health.

Despite the rapid proliferation of WDs in healthcare and their promising potential for objective applications, several limitations persist. While these devices can collect vast amounts of physiological data, the accuracy and reliability of this data are often constrained by sensor performance. The high incidence of false-positive results may cause harm, and over-reliance on smartwatches, coupled with inadequate patient education, could potentially strain the doctor–patient relationship.[46] Furthermore, the lack of standardized data across different devices compromises data comparability and comprehensive utilization. The absence of standardized regulatory measures for WDs leads to compatibility issues between different devices,[47] further complicated by the lack of uniform standards for the data they generate. The extensive collection of health data by WDs also raises significant concerns regarding privacy and security.[48] Misuse or leakage of this information could have severe consequences for users.

However, as technology progresses, anticipated improvements in sensor accuracy, data security measures, and regulatory frameworks are expected to further enhance the efficacy and safety of these devices. Furthermore, the integration of artificial intelligence and machine learning in data analysis enhances the interpretability of health metrics, enabling more personalized healthcare interventions. WDs in healthcare facilitate continuous vital sign monitoring. By combining big data processing and displaying the information on mobile devices, WDs serve dual purposes: on one hand, they empower individuals with consistent health status updates, fostering awareness and proactive health management; on the other hand, health service providers such as doctors or health managers can leverage the analyzed data to optimize treatment plans and enhance therapeutic outcomes. Therefore, while the limitations are noteworthy, the transformative potential of WDs in fostering health awareness and improving patient outcomes is substantial.

Strength and limitation

This study presents a visual overview of the publication trends in the field of WDs in medicine, including the number of publications, countries and regions, research institutions, journals, authors, and keywords. It provides scholars with a multidimensional understanding of the basic information in this field, serving as a reference for future research and exploration. However, there are certain limitations, we only retrieved and analyzed literature from the WOS Core database before July 5, 2023. Due to the real-time dynamic updates in the WoSCC database and the ongoing development of wearable technology, the research can only illustrate the development and current research hotspots so far and cannot predict whether another peak will occur. Our classification of medical disciplines during article retrieval may not be rigorous enough, resulting in incomplete data samples. Additionally, during the article retrieval process, we observed that certain authors employed specific patterns in their selection of subject terms or keywords. While this may have led to the omission of some relevant articles from our search results, it did not influence the overall direction or outcomes of the research. Further research should expand the scope of literature retrieval and databases and employ more standardized discipline classifications. We recommend detailing the number of researchers involved in screening each record and the reports retrieved to enhance transparency and reliability. Ensuring that researchers work independently can also minimize bias and improve the validity of findings. Future studies should provide clear documentation of the selection criteria and screening processes, specifying the number of participating researchers and whether assessments were conducted independently or collaboratively. In summary, we believe that the visual results provided by CiteSpace indicate that scholars worldwide are increasingly interested in WDs. We have provided experts with an opportunity for visual pattern recognition and trend analysis.

Conclusions

This bibliometric analysis study has identified the main research trajectories in the field of WDs in medicine. We have visually described the co-occurrence and co-citation networks of publications in this research field, providing insights into the characteristics and emerging trends over the past 20 years. However, the development of research and collaboration between countries/regions and institutions is limited, especially with significant differences in research levels between Asian and Western countries. Therefore, strengthening cooperation and communication between different countries/regions and institutions will contribute to the further development of this field. In the field of medicine, the journal that publishes the most articles related to WDs is PLOS One. Keyword burst analysis indicates that mobile app, mobile phone, and neural network are current research hotspots. Our co-occurrence analysis shows that research directions such as physical activity, sleep monitoring, AF, and gait analysis remain recent research hotspots and frontiers. The emergence of new technologies such as blockchain, cloud computing, and 5G is driving the development of WDs in the field of medicine.

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References

1. Amft O and Lukowicz P. From backpacks to smartphones: past, present, and future of wearable computers. *IEEE Pervasive Comput* 2009; 8: 8–13.
2. Carpi F and De Rossi D. Electroactive polymer-based devices for e-textiles in biomedicine. *IEEE Trans Inf Technol Biomed* 2005; 9: 295–318.
3. Grossman P. The LifeShirt: a multi-function ambulatory system monitoring health, disease, and medical intervention in the real world. *Stud Health Technol Inform* 2004; 108: 133–141.
4. Young AJ and Ferris DP. State of the art and future directions for lower limb robotic exoskeletons. *IEEE Trans Neural Syst Rehabil Eng* 2017; 25: 171–182.
5. Chang C, Bang K, Wetzstein G, et al. Toward the next-generation VR/AR optics: a review of holographic near-eye displays from a human-centric perspective. *Optica* 2020; 7: 1563–1578.
6. Perez MV, Mahaffey KW, Hedlin H, et al. Large-scale assessment of a smartwatch to identify atrial fibrillation. *N Engl J Med* 2019; 381: 1909–1917.
7. Lee H, Choi TK, Lee YB, et al. A graphene-based electrochemical device with thermoresponsive microneedles for diabetes monitoring and therapy. *Nat Nanotechnol* 2016; 11: 566.
8. Haghi M, Thurow K and Stoll R. Wearable devices in medical internet of things: scientific research and commercially available devices. *Healthc Inform Res* 2017; 23: 4–15.
9. Pang C, Lee C and Suh K-Y. Recent advances in flexible sensors for wearable and implantable devices. *J Appl Polym Sci* 2013; 130: 1429–1441.
10. Lu L, Zhang J, Xie Y, et al. Wearable health devices in health care: narrative systematic review. *Jmir Mhealth Uhealth* 2020; 8(11): e18907.
11. Wang C, Wu X and Qi H. A comprehensive analysis of E-health literacy research focuses and trends. *Healthcare* 2022; 10(1): 66.
12. Zhang Z, Tan J, Jin W, et al. Severe fever with thrombocytopenia syndrome virus trends and hotspots in clinical research: a bibliometric analysis of global research. *Front Public Health* 2023; 11: 1120462.
13. Chen C and CiteSpace II. Detecting and visualizing emerging trends and transient patterns in scientific literature. *J Am Soc Inf Sci Technol* 2006; 57: 359–377.
14. Synnestvedt MB, Chen C and Holmes JH. CiteSpace II: visualization and knowledge discovery in bibliographic databases. *AMIA Annu Symp Proc AMIA Symp* 2005: 724–728.
15. Ravi D, Wong C, Deligianni F, et al. Deep learning for health informatics. *IEEE J Biomed Health Inform* 2017; 21: 4–21.

16. Bhatt JM, Lin HW and Bhattacharyya N. Prevalence, severity, exposures, and treatment patterns of tinnitus in the United States. *JAMA Otolaryngol-Head Neck Surg* 2016; 142: 959–965.
17. Beniczky S, Conradsen I, Henning O, et al. Automated real-time detection of tonic-clonic seizures using a wearable EMG device. *Neurology* 2018; 90: E428.
18. Dehkordi P, Khosrow-Khavar F, Di Rienzo M, et al. Comparison of different methods for estimating cardiac timings: a comprehensive multimodal echocardiography investigation. *Front Physiol* 2019; 10: 1057.
19. Inan OT, Pouyan MB, Javaid AQ, et al. Novel wearable seismocardiography and machine learning algorithms can assess clinical status of heart failure patients. *Circulation-Heart Failure* 2018; 11(1): e004313.
20. Wiens AD, Etemadi M, Roy S, et al. Noninvasive assessment of ventricular function and hemodynamics: wearable Ballistocardiography. *IEEE J Biomed Health Inform* 2015; 19: 1435–1442.
21. Meyer N, Kerz M, Folarin A, et al. Capturing rest-activity profiles in schizophrenia using wearable and mobile technologies: development, implementation, feasibility, and acceptability of a remote monitoring platform. *JMIR Mhealth Uhealth* 2018; 6(10): e188. doi: 10.2196/mhealth.8292.
22. Cheng K, Guo Q, Yang W, et al. Mapping knowledge landscapes and emerging trends of the links between bone metabolism and diabetes mellitus: a bibliometric analysis from 2000 to 2021. *Front Public Health* 2022; 10: 918483.
23. Rubow R and Swift E. A microcomputer-based wearable biofeedback device to improve transfer of treatment in parkinsonian dysarthria. *J Speech Hear Disord* 1985; 50: 178–185.
24. Axisa F, Schmitt PM, Gehin C, et al. Flexible technologies and smart clothing for citizen medicine, home healthcare, and disease prevention. *IEEE Trans Inf Technol Biomed* 2005; 9: 325–336.
25. Hao Y and Foster R. Wireless body sensor networks for health-monitoring applications. *Physiol Meas* 2008; 29: R27–R56.
26. Chan M, Campo E, Esteve D, et al. Smart homes—current features and future perspectives. *Maturitas* 2009; 64: 90–97.
27. Kumar S, Nilsen WJ, Abernethy A, et al. Mobile health technology evaluation the mHealth evidence workshop. *Am J Prev Med* 2013; 45: 228–236.
28. Krishna S, Boren SA and Balas EA. Healthcare via cell phones: a systematic review. *Telemed J E Health* 2009; 15: 231–240.
29. Patrick K, Griswold WG, Raab F, et al. Health and the mobile phone. *Am J Prev Med* 2008; 35: 177–181.
30. Riley WT, Rivera DE, Atienza AA, et al. Health behavior models in the age of mobile interventions: are our theories up to the task? *Transl Behav Med* 2011; 1: 53–71.
31. Chiauzzi E, Rodarte C and DasMahapatra P. Patient-centered activity monitoring in the self-management of chronic health conditions. *BMC Med* 2015; 13: 77.
32. Mercer K, Giangregorio L, Schneider E, et al. Acceptance of commercially available wearable activity trackers among adults aged over 50 and with chronic illness: a mixed-methods evaluation. *JMIR Mhealth Uhealth* 2016; 4: 168–184.
33. Pasluosta CF, Gassner H, Winkler J, et al. An emerging era in the management of Parkinson's disease: wearable technologies and the internet of things. *IEEE J Biomed Health Inform* 2015; 19: 1873–1881.
34. Martin SS, Feldman DI, Blumenthal RS, et al. mActive: a randomized clinical trial of an automated mHealth intervention for physical activity promotion. *J Am Heart Assoc* 2015; 4(11): e002239.
35. Wen D, Zhang X, Liu X, et al. Evaluating the consistency of current mainstream wearable devices in health monitoring: a comparison under free-living conditions. *J Med Internet Res* 2017; 19(3): e68. doi:10.2196/jmir.6874
36. Del Din S, Godfrey A and Rochester L. Validation of an accelerometer to quantify a comprehensive battery of gait characteristics in healthy older adults and Parkinson's disease: toward clinical and at home use. *IEEE J Biomed Health Inform* 2016; 20: 838–847.
37. Ravi D, Wong C, Lo B, et al. A deep learning approach to on-node sensor data analytics for mobile or wearable devices. *IEEE J Biomed Health Inform* 2017; 21: 56–64.
38. Katsigiannis S and Ramzan N. DREAMER: a database for emotion recognition through EEG and ECG signals from wireless low-cost off-the-shelf devices. *IEEE J Biomed Health Inform* 2018; 22: 98–107.
39. Fan X, Yao Q, Cai Y, et al. Multiscaled fusion of deep convolutional neural networks for screening atrial fibrillation from single lead short ECG recordings. *IEEE J Biomed Health Inform* 2018; 22: 1744–1753.
40. Olgin JE, Pletcher MJ, Vittinghoff E, et al. Wearable cardioverter-defibrillator after myocardial infarction. *N Engl J Med* 2018; 379: 1205–1215.
41. Turakhia MP, Desai M, Hedlin H, et al. Rationale and design of a large-scale, app-based study to identify cardiac arrhythmias using a smartwatch: the apple heart study. *Am Heart J* 2019; 207: 66–75.
42. Wasserlauf J, You C, Patel R, et al. Smartwatch performance for the detection and quantification of atrial fibrillation. *Circ-Arrhythmia Electrophysiol* 2019; 12(6): e006834.
43. Bent B, Goldstein BA, Kibbe WA, et al. Investigating sources of inaccuracy in wearable optical heart rate sensors. *Npj Digital Med* 2020; 3: 18.
44. Rose DP, Ratterman ME, Griffin DK, et al. Adhesive RFID sensor patch for monitoring of sweat electrolytes. *IEEE Trans Biomed Eng* 2015; 62: 1457–1465.
45. Bumgarner JM, Lambert CT, Hussein AA, et al. Smartwatch algorithm for automated detection of atrial fibrillation. *J Am Coll Cardiol* 2018; 71: 2381–2388.
46. Predel C and Steger F. Ethical challenges with smartwatch-based screening for atrial fibrillation: putting users at risk for marketing purposes? *Front Cardiovasc Med* 2020; 7: 615927.
47. Awad S, Aljuburi L, Lumsden RS, et al. Connected health in US, EU, and China: opportunities to accelerate regulation of connected health technologies to optimize their role in medicines development. *Front Med (Lausanne)* 2023; 10: 1248912.
48. Canali S, Schiaffonati V and Aliverti A. Challenges and recommendations for wearable devices in digital health:

data quality, interoperability, health equity, fairness. *PLOS Digit Health* 2022; 1: e0000104.

49. Majumder S, Mondal T and Deen MJ. Wearable sensors for remote health monitoring. *Sensors (Basel)* 2017; 17(1): 130. doi:10.3390/s17010130 .
50. Crea S, Donati M, De Rossi SMM, et al. A wireless flexible sensorized insole for gait analysis. *Sensors* 2014; 14: 1073–1093.
51. Zhao S, Liu R, Fei C, et al. Flexible sensor matrix film-based wearable plantar pressure force measurement and analysis system. *PLOS One* 2020; 15(8): e0237090.
52. Boto E, Holmes N, Leggett J, et al. Moving magnetoencephalography towards real-world applications with a wearable system. *Nature* 2018; 555: 657–661.
53. Mishra S, Kim Y-S, Intarasirisawat J, et al. Soft, wireless periocular wearable electronics for real-time detection of eye vergence in a virtual reality toward mobile eye therapies. *Sci Adv* 2020; 6(11): eaay1729.
54. Hu HZ, Feng XB, Shao ZW, et al. Application and prospect of mixed reality technology in medical field. *Curr Med Sci* 2019; 39: 1–6.
55. Nelson BW and Allen NB. Accuracy of consumer wearable heart rate measurement during an ecologically valid 24-hour period: intraindividual validation study. *JMIR Mhealth Uhealth* 2019; 7(3): e10828. doi:10.2196/10828.
56. Luo N, Dai W, Li C, et al. Flexible piezoresistive sensor patch enabling ultralow power cuffless blood pressure measurement. *Adv Funct Mater* 2016; 26: 1178–1187.