Research Trends in Wearable Devices: A Bibliometric Assessment

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ABSTRACT: *Wearable devices or wearable technology are designed to be worn on the body, including smartwatches, fitness trackers, smart glasses, and headphones, primarily used for tracking activities and health monitoring. The paper aims to provide a comprehensive bibliometric analysis and mapping of the intellectual structure of wearable device research. The SCOPUS-based study retrieved 7172 records spanning 26 years (1999-2023) using relevant keywords associated with wearable devices. The findings of the study unearth that there has been a significant increase in publications on wearable devices since 2012. The United States and China emerged as leading contributors. Sensors Journal was identified as the most productive journal. The thematic analysis shows a significant technological advancement in wearable devices, which are applied prominently in health monitoring. The cluster analysis reveals the research hotspots in health-related wearable devices, wearable sensors powered by machine learning and deep learning, wearable electronics, smart clothing and textiles, and human activity monitoring. This study offers a bibliometric qualitative overview of wearable devices and provides quantitative research by providing insights into the field's intellectual structure and thematic evolution. The study contributes to the existing knowledge domain by identifying key trends, influential contributors, and key thematic areas for future research.*

Keywords: Wearable Devices, Wearable Technology, Smart Textiles, Bibliometric Analysis

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1. Introduction

Information and Communication Technology (ICT), including mobile technology, has significantly reduced size and speed. The transformation is from niche services or products to ubiquitous computing. The increase in handheld interconnected devices has become integral to human life. The bulky computers have now shrunk into a palm-top, and the world is witnessing new trends in the mobile device market. There is a huge technological shift and advancement from handheld mobile devices to wearable devices (Das et al., 2018; Ometov et al., 2021). Wearable devices, categorized as smart bands, jewellery, clothing, and patches, have become an integral part of human life. The benefits of such wearable devices include they collect real-time data 24x7, which is analyzed and interpreted to improve the quality of life (Luczak et al., 2020; Ometov et al., 2021; Seneviratne et al., 2017).

The principle behind wearable devices or wearable technology is that they include small electronic or mobile devices equipped with wireless technology that can be put on the human body. It generally has the feature of monitoring or scanning the human body and giving biofeedback or monitoring sensory-dependent physiological functions (Khan et al., 2021). Historically, the evolution of wearable technology has its roots in the 13th century, with Roger Bacon's invention of spectacles marking the inception of wearables as functional devices (Starner, 1999). The 20th century witnessed significant advancements in wearable technology, particularly during the World Wars. The development of the Pigeon Camera by Julius Neubronner in 1907 (Erickson, 2013), later adapted for military use, the introduction of wristwatches for precise military operations during World War II, underscored the growing importance of wearables in various fields. Morton Heilig's 1960 invention of the "Stereophonic Television Head-Mounted Display" marked the beginning of immersive virtual reality technology, expanding the potential of wearables beyond mere functionality (Heilig, 1994; Ometov et al., 2021)Fewer improvements in the 1970s and 1980s saw the commercialization of wearable computing, and these innovations paved the way for more advanced wearables, which explored augmented reality. The early 2000s brought a surge in consumer-focused wearables, such as the Fitbit and the GoPro camera, which emphasized health tracking and portable video recording. (Evers, 2015). By 2015, wearable technology had become integral to daily life, with iOS and Android-based applications embedded in the watches focusing on improved healthcare. The global market of wearable devices has increased significantly, driven by the increasing adoption of smartwatches, fitness trackers, and other health-related trackers, as well as the advancement of artificial intelligence and the Internet of Things within these devices (Nandi et al., 2022).

Wearable device research has seen significant growth, yet comprehensive studies on the overall knowledge structures in this field still need to be completed. Some prior studies have focused on specific industries or uses, such as healthcare or safety management in construction, or have used keywords like smartwatches and smart glasses to narrow their scope—a Web of Science-based study by Kageyama et al. (2022) highlighted the research trends limited to the United States and China. In contrast, another study by Wang & Qi (2021) presented the knowledge structure of the domain. These approaches limit the breadth of research and narrow their focus, offering only qualitative trend analyses of specific geographic locations or conditions, such as health care, and failing to cover the wearable device field. The challenge lies in the diversity of fields encompassed by wearable device research, making it difficult to view the domain comprehensively. By not limiting the research to specific industries or keywords, this study aims to quantitatively and qualitatively organize and clarify the entire research domain, providing a more complete understanding of the intellectual structure surrounding wearable devices.
With this outline, this study aims to answer the following research questions.

1. What is the research output of wearable devices, and what has been its trend over time?

2. Who are the most prolific authors, institutions, and countries in wearable device research, and what is their impact on the field?

3. What are the most common thrust areas of research on wearable devices, and how have these evolved?

2. Methods

The study is based on the SCOPUS multidisciplinary database. SCOPUS is an essential source of data for literature review and bibliometric analysis, and it is used globally with comprehensive coverage of literature in science, technology, management, humanities, and social sciences.

2.1. Search Strategy

The literature on wearable devices has been retrieved from the SCOPUS database by searching the TITLE field of the database. Hyland and Zou (2022) opine that the title is a significant part of the academic genre, presenting the key message of the research. The researcher often refers to an article's title for further reading and citation in future research work. Therefore, the paper's title is considered a key message communicator of the research. In bibliometric analysis, sometimes, only the title field is used to search data to avoid redundancy and ensure specificity and relevance filtering. Wearable devices are a multidisciplinary field, and there might be a chance of redundant data from large data sets. Managing large volumes of data by using other fields, such as abstract or keyword fields, may be difficult in a single study. The PRISMA flow has been used to collect data (Moher et al., 2009). The keywords related to wearable devices or wearable technology have been used to conduct a search using the following search string:

(TITLE(" Wearable technology " OR " Fitness trackers " OR " Smartwatches " OR " Smart watches " OR " Health monitoring devices " OR " Wearable sensors " OR " Activity trackers " OR " Wearable health tech " OR " Smart clothing " OR " Wearable fitness devices " OR " Medical wearables " OR " Wearable ECG monitors " OR " Biometric wearables " OR " Wearable health monitors " OR " Wearable tech trends " OR " Wearable device market " OR " Wearable electronics " OR " IoT wearables " OR " Augmented reality wearables " OR " Wearable medical devices " OR " Wearable device security ")

2.2. Data Collection and Cleaning

The search string described above resulted in 7172 records spread over twenty-six years (1999-2023). Many records after extraction may lack uniformity and consistency, so they need proper cleaning and harmonization. Each record was thoroughly checked for complete metadata elements and consistency, an essential requirement for bibliometric analysis. Bibliomagika v2.9 (Ahmi, 2024) and OpenRefine (Ahmi, 2023) A tool was used to clean and harmonize the data sets, ensuring that each record had complete metadata elements. Erratum, corrections, and retracted document types were excluded from the data analysis.

2.3. Bibliometric Measures

The bibliometric analysis comprises performance analysis of authors, institutions, and countries. It also includes the productivity analysis of journals, descriptive qualitative analysis comprising citation metrics, and bibliometric mapping covering the relationships between different domains. In this study, the bibliometric analysis includes annual productivity, prolific authors, institutions, country, journals, most cited articles, and thematic analysis using Bibliometrix, and VoS Viewer tools (Van Eck & Waltman, 2010, 2014).

3. Results

3.1. Documents Profiles

Table 1 provides a detailed document profile of literature related to wearable devices, covering data from 1999 to 2023 (26 years). The twenty-six-year duration reflects the development and academic interest in wearable devices over time. During the period, many research studies (N=7172) were published on wearable devices, indicating a well-established field with a strong research foundation. These publications have been contributed by 33,653 authors, with an average of 4.69 authors per paper, showing a broad collaborative academic community**.** Of the publications, 6,191 (86.72%) papers have been cited, indicating that most of the research has been influential enough to be referenced by other works. These cited papers have accumulated 2,03,562 citations, with an average citation per paper of 28.38, demonstrating the impact and relevance of this body of work within the research community. The overall *h*-index (Hirsch, 2005) The number of these publications is 180, which means that there are 180 papers with at least 180 citations each, reflecting both the authors' productivity and citation impact. The *g*-index (300) and *m*-index (6.923) are also given in the table, portraying a vibrant and impactful research field around wearable devices characterized by high citation rates, collaborative and active authorship, and a strong presence of influential papers.

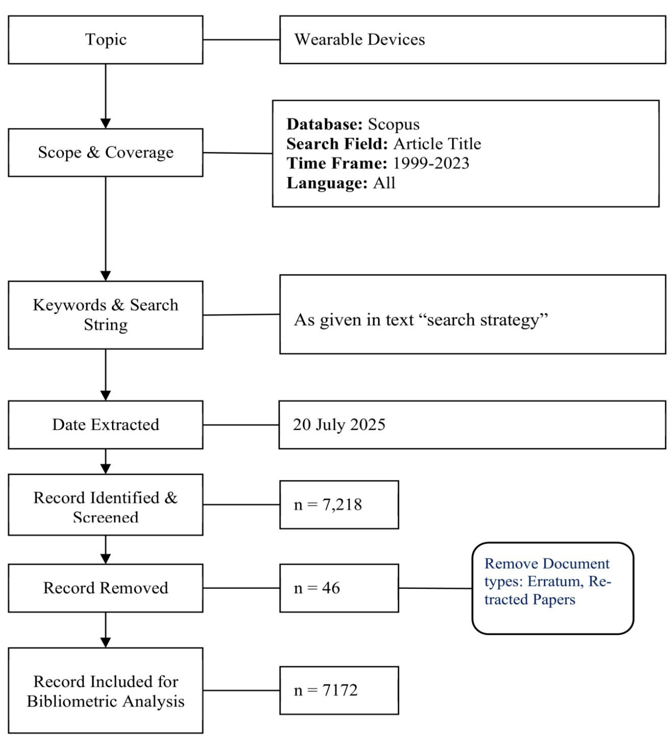

Figure 1. Flow diagram of the search process

Table 1. Document Profile Of The Literature On Wearable Devices

Main Information	**Data**
Publication Years	1999 - 2023
Total Publications	7172
Citable Year	26
Number of Contributing Authors	33653
Number of Cited Papers	6191
Total Citations	203,562
Citation per Paper	28.38
Citation per Cited Paper	32.88
Citation per Year	8481.75
Citation per Author	6.05
Author per Paper	4.69
Citation sum within h-Core	130,332
h-index	180
g-index	300
m-index	6.923

Table 2. Subject Area of wearable devices

Subject Area	**Total Publications**	**Percentage (%)**
Engineering	3249	45.30%
Computer Science	3200	44.62%
Medicine	1767	24.64%
Materials Science	1175	16.38%
Physics and Astronomy	1172	16.34%
Chemistry	847	11.81%
Biochemistry, Genetics and Molecular Biology	776	10.82%
Mathematics	519	7.24%
Social Sciences	469	6.54%
Health Professions	368	5.13%
Chemical Engineering	358	4.99%
Decision Sciences	263	3.67%
Energy	246	3.43%

Business, Management and Accounting	211	2.94%
Environmental Science	163	2.27%
Neuroscience	160	2.23%
Multidisciplinary	106	1.48%
Nursing	106	1.48%
Psychology	96	1.34%
Arts and Humanities	78	1.09%
Agricultural and Biological Sciences	42	0.59%
Economics, Econometrics and Finance	41	0.57%
Immunology and Microbiology	33	0.46%
Pharmacology, Toxicology and Pharmaceutics	33	0.46%
Earth and Planetary Sciences	28	0.39%
Veterinary	9	0.13%

(Note: The articles may fall into multiple subject areas, so the percentage share may be more than 100%)

SCOPUS classifies its data into twenty-seven major subject disciplines and 330 sub-disciplines to comprehensively cover each subject domain (Thelwall & Pinfield, 2024). The wearable devices fall under technology, so the majority of the publications have been classified under Engineering (45.30%), followed by Computer Science (44.62%) and Medicine (24.64%). This indicates that authors from these three subject domains are actively publishing their research in these domains. Due to its multidisciplinary research field, there is a fair chance of overlapping the subject domain where the same publication may fall under different subject categories (Table 2).

3.2. Publication Trends

With single publication in the eighties and nineties, continued publication trends can be observed from 1999 onwards and included in the study. Table 3 illustrates the temporal growth of publications on wearable devices. Up to 2012, the literature on wearable devices was below a hundred documents per year; after that, exponential growth can be observed, showing research on technical evolution and quite a sought-after domain. This increase can be evident due to enhanced research activity, especially in computer science, sports, and medicine. The number of publications on a year-to-year basis is increasing. The research work published in the years 2018 and 2019 has been the most cited works (Figure 2)

Table 3. Publication by Year

Year	TP	NCA	NCP	TC	C/P	C/CP
1999	3	10	3	316	105.33	105.33
2000	7	23	7	206	29.43	29.43
2001	8	26	7	200	25.00	28.57
2002	9	27	9	627	69.67	69.67
2003	16	50	14	1236	77.25	88.29
2004	12	34	12	469	39.08	39.08
2005	27	94	24	1598	59.19	66.58

2006	46	158	42	2558	55.61	60.90
2007	42	164	36	757	18.02	21.03
2008	43	177	40	1600	37.21	40.00
2009	64	200	55	2235	34.92	40.64
2010	57	224	51	4320	75.79	84.71
2011	89	358	82	3290	36.97	40.12
2012	73	291	64	4664	63.89	72.88
2013	107	396	90	5680	53.08	63.11
2014	168	646	146	9861	58.70	67.54
2015	336	1270	291	17475	52.01	60.05
2016	477	1984	439	22593	47.36	51.46
2017	579	2538	538	19864	34.31	36.92
2018	652	2848	576	23178	35.55	40.24
2019	724	3534	670	23549	32.53	35.15
2020	785	3861	723	21990	28.01	30.41
2021	862	4307	782	18364	21.30	23.48
2022	987	5223	827	11772	11.93	14.23
2023	999	5210	663	5160	5.17	7.78
Total	7172	33653	6191	203562	28.38	32.88

TP=total publications; NCA=Number of contributing authors; NCP=number of cited publications; TC=total citations; C/P=average citations per publication; C/CP=average citations per cited publication; h=h-index; g=g-index; m=m-index.

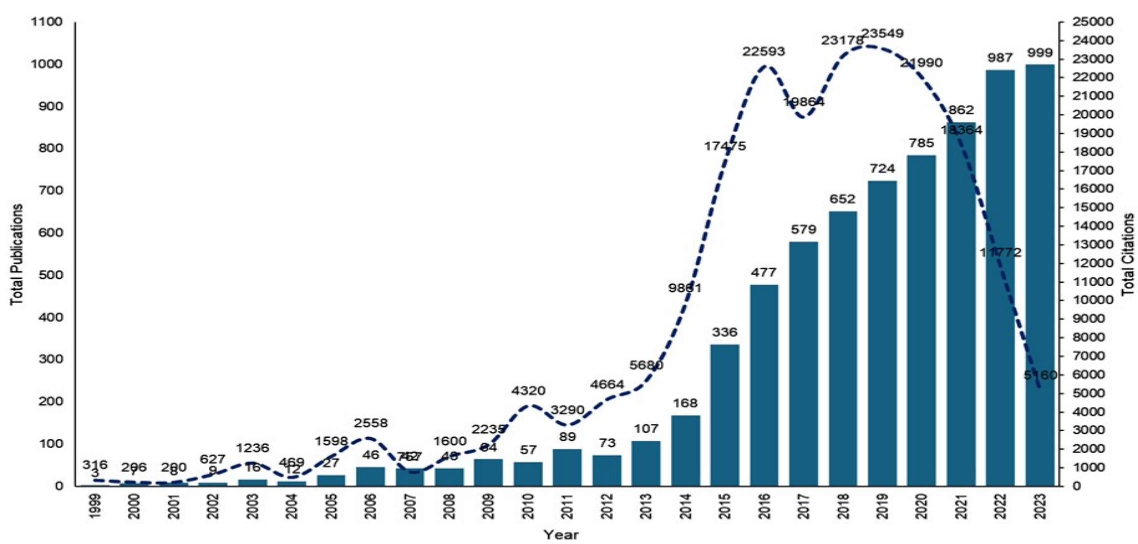

Figure 2. Total Publications and Citations by Year

3.3. Publications by Authors

The articles on wearable devices were contributed by 33,653 (average=4.69 papers per author), either singly or in collaboration. Of 7172 documents, 462 (6.44%) were published as single-authored papers, and 6678 documents (93.11%) were published in joint authorship. The contribution of the top ten authors who have contributed fifteen or more articles on wearable devices is given in Table 4. The analysis is carried out based on total publication (TP), total citation (TC), Average Citation Per Paper (ACPP), and *h*-Index. Among the most productive authors publishing papers on wearable devices, Bonato, P. from Spaulding Rehabilitation Hospital Network United States has published maximum publications (TP = 42, TC = 4544, ACPP=108.19 citations and *h*-index = 25). It can be observed from Figure 3 that Bonato P. has been working on wearable devices and deep learning, and the author is still active in publishing. The second most productive author is Liu, T. from the State Key Laboratory of Fluid Power and Mechatronic Systems, China (TP=22; TC=1601; ACPP=72.77 and *h*-Index=11). The author's major research area is deep learning. The third most productive author is Najafi, B. from Baylor College of Medicine, United States (TP=22; TC=930; ACPP=42.27 and *h*-Index=16). The author is more active in wearable technology and gait analysis. It is observed from Figure 4 that Patel, S. from Ôura Health Ltd, United States, has been active until 2019, and the publications are third most highly cited with an ACPP 135. 55 citations per paper. Similarly, Wang, Z.L. from the Chinese Academy of Sciences, China (TP=18; TC=5538 and *h*-Index=18) is the highest citation and ACPP of 307.67. Two authors from Thailand, Jitpattanakul, A. and Mekruksavanich, S. (TP=16), have been active in recent years.

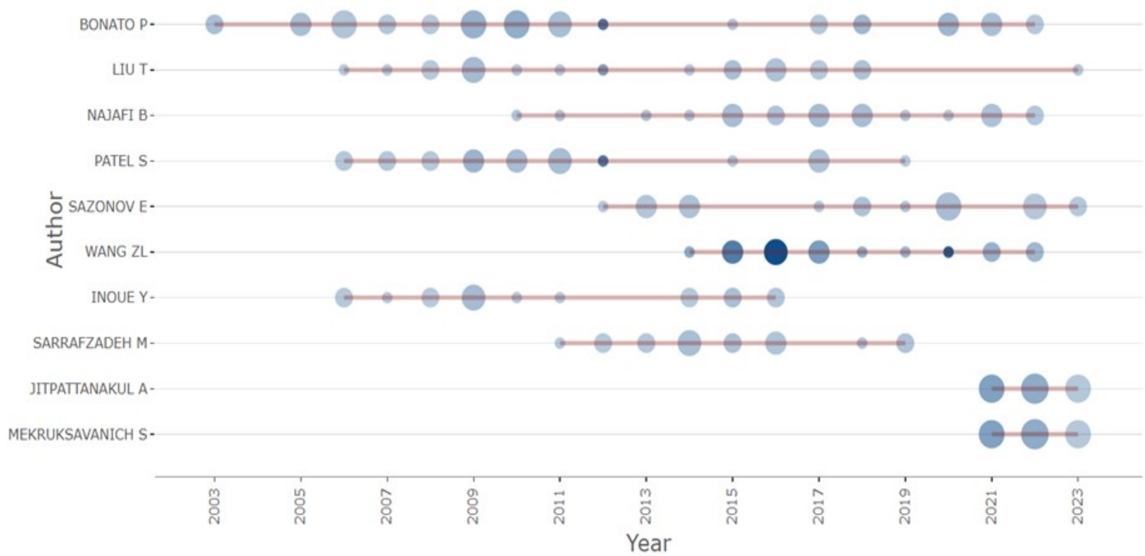

Figure 3. Active authors and publication trends in wearable technology

3.4. Publications by Countries

Table 6 presents the top 10 countries with three hundred or more articles contributing 86.89% of the documents on wearable devices. As of 2023, the United States has contributed the highest number of articles (26.38% share), followed by China (16.72% share) and the United Kingdom (8.49% share). United States tops the table regarding total citations (TC=75530 citations) and *h*-Index (*h*-index=122). The publications from India have the least citations (TC=6156) for its 431 publications (*h*-Index=40). Japan has the lowest Hirsh Index value (*h*-index=37) for its 318 publications and 7371 citations.

Table 6. Top 10 Countries contributed to the publications on wearable devices

Country	TP	%Share	TC	ACPP	h
United States	1892	26.38	75,530	39.92	122
China	1199	16.72	48,568	40.51	108
United Kingdom	609	8.49	16,243	26.67	66

India	431	6.01	6,156	14.28	40
South Korea	402	5.61	18,584	46.23	67
Italy	386	5.38	10,032	25.99	47
Germany	363	5.06	9,498	26.17	49
Australia	329	4.59	11,306	34.36	56
Japan	318	4.43	7,371	23.18	37
Canada	303	4.22	9,855	32.52	44
Total Publication	6232	86.89	213,143	34.20	

TP=total publications; TC=total citations; ACPP=average citations per publication; h=*h*-index

Table 5. Most Productive Authors

Author's Name	**Current Affiliation**	**Country**	**TP**	**TC**	**ACPP**	***h***
Bonato, P.	Spaulding Rehabilitation Hospital Network	United States	42	4544	108.19	25
Liu, T.	State Key Laboratory of Fluid Power and Mechatronic Systems	China	22	1601	72.77	11
Najafi, B.	Baylor College of Medicine	United States	22	930	42.27	16
Patel, S.	Ōura Health Ltd	United States	22	2982	135.55	16
Sazonov, E.	University of Alabama	United States	22	450	20.45	11
Wang, Z.L.	Chinese Academy of Sciences	China	18	5538	307.67	18
Inoue, Y.	Kochi University of Technology	Japan	17	617	36.29	9
Sarrafzadeh, M.	UCLA Samueli School of Engineering Los Angeles	United States	17	552	32.47	12
Jitpattanakul, A.	King Mongkut's University of Technology North Bangkok	Thailand	16	393	24.56	7
Mekruksavanich, S.	University of Phayao	Thailand	16	393	24.56	7

TP=total number of publications; TC=total citations; ACPP=average citations per publication; *h*=h-index

3.5. Publications by Institutions

The publication by institutions in the domain of wearable technology has been assessed using the parameters of total publication (TP), total citations (TC), average citations per paper (ACPP), and *h*-index. The top eleven institutions with more than fifty publications are given in Table 5. It is observed that the Ministry of Education of the People's Republic of China (TP=151; TC=7707; ACPP=51.04 and *h*-Index=43) is the most influential institution, followed by Chinese Academy of Sciences, China (TP=141; TC=11918; ACPP=84.52 and *h*-Index=51) and Georgia Institute of Technology, USA (TP=73; TC=8284; ACPP=113.48 and *h*-Index=36). The Chinese Academy of Sciences publications are highly cited, followed by the Georgia Institute of Technology, USA.

Table 6. Most productive institutions with a minimum of fifty publications

Affiliation	**TP**	**TC**	**ACPP**	**h-Index**
Ministry of Education of the People's Republic of China	151	7707	51.04	43
Chinese Academy of Sciences, China	141	11918	84.52	51
Georgia Institute of Technology, USA	73	8284	113.48	36
Harvard Medical School, USA	69	5333	77.29	31
Imperial College London, UK	62	2797	45.11	26
Zhejiang University, China	58	4003	69.02	28
University of Chinese Academy of Sciences, China	56	3355	59.91	30
University of Michigan, Ann Arbor, USA	54	1672	30.96	24
Tsinghua University, China	53	3624	68.38	29
National University of Singapore, Singapore	52	2493	47.94	21
Massachusetts Institute of Technology, USA	51	3543	69.47	20

TP=total publications; TC=total citations; ACPP=average citations per publication; h=*h*-index

3.6. Publications by Source Titles

Table 7 contains highly productive journals, books, or conference series. As the domain is more focused on computing and sensor systems, it is also reflected in the journal's title. *Sensors* is the most productive journal, and it publishes the most articles on wearable devices. There are two book series and two conference series where most publications on wearable devices appeared. The articles published in *Sensors* (Switzerland) are the most cited, with overall citations of 10454 (ACPP=62.23 citations). The value of journals is commonly associated with the number of citations scored by the articles published in it and its Impact Factor, an average of total citations with total publications in the last two years. (Garfield, 1955, 1999) And CiteScore, calculated with a duration of three years, in comparison to impact factor, which uses two years duration (Teixeira Da Silva, 2020)On this parameter, ACS Applied Materials and Interfaces has the highest CiteScore of 16, followed by JMIR mHealth and uHealth (12.6) and Conference on Human Factors in Computing Systems—Proceedings (8.3).

3.7. Co-word clustering based on Keywords

The central theme of any article is generally represented by the author's keyword, which is provided by the author in their paper. (Lu et al., 2020). The thematic analysis approach is based on the co-occurrence of the author's keyword in wearable devices. A bibliometric software, VOSviewer, is used to create a co-occurrence network. The software draws a graphical network depicting the strength between two keywords. (Van Eck & Waltman, 2010). In wearable devices, the analysis was carried out on the keyword frequency of co-occurrence with twenty-five or more with full counting. The network visualisation in Figure 4 is based on 86 keywords meeting the criteria. To maintain the quality, keywords were cleaned and harmonised using OpenRefine Software. (Ahmi, 2023).

Table 7. Most active source titles that published 20 or more documents

Source Title	TP	TC	C/P	*h*	Cite Score 2023
Sensors	211	3163	14.99	25	7.3
Sensors (Switzerland)	168	10454	62.23	49	7.7
Lecture Notes in Computer Science (including Lecture Notes in AI and BI)	147	1318	8.97	17	16
IEEE Sensors Journal	88	4904	55.73	32	12.6
Proceedings of the Annual International Conference of the IEEE EMBS	87	1282	14.74	20	7.3
ACM International Conference Proceeding Series	81	744	9.19	15	8.3
JMIR mHealth and uHealth	77	3284	42.65	30	2.6
ACS Applied Materials and Interfaces	74	3948	53.35	33	2.2
Conference on Human Factors in Computing Systems - Proceedings	61	2141	35.10	28	1.5
Advances in Intelligent Systems and Computing	51	305	5.98	9	0.9

TP=total number of publications; NCA=Number of contributing authors; NCP=number of cited publications; TC=total citations; C/P=average citations per publication; C/CP=average citations per cited publication; h=h-index; g=g-index; m=m-index.

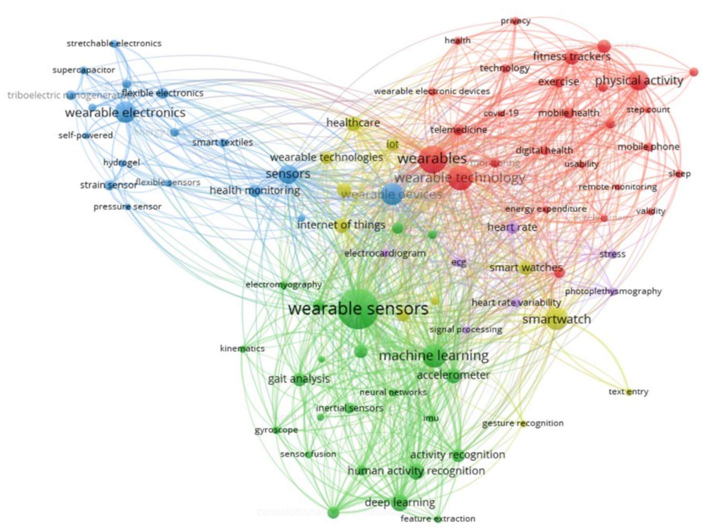

Figure 4. Network visualisation of the author keywords co-occurrence

The Network visualisation created using VoS viewer software has five clusters. The circle represents the keywords, and the lines represent the occurrence of the keywords together. The size of the circle represents the frequency, while the thickness of the line represents the strength of the pairing of words together. The network's colour (red, green, blue, yellow, and purple) represents the grouping of the keywords within the theme.

Red, green, and blue colour clusters are more massive than yellow and purple. The red cluster, represented by twenty-seven keywords, covers the topic associated with wearables, wearable technology, smartphones, monitoring physical activity, telemedicine, fitness trackers, activity trackers, exercise, digital health, mobile health, and Fitbit. Thus, it can be classified as health-related wearable devices and technology. It is quite prominent that people are becoming more conscious about their health and interested in monitoring their daily activities with the help of wearable devices. These include heartbeat monitoring (Bai et al., 2018), obesity or overweight control (Sushames et al., 2016), and other health-related complications. Mobile phone-controlled wearable devices such as smartphones are quite helpful and are gaining popularity. (Jin et al., 2020).

The green cluster represents the wearable sensors powered by Machine Learning and Deep Learning methods. The technological enhancement in wearable devices powered by sensors and integrated with machine learning and deep learning algorithms enhances the impact, especially in health monitoring. The cluster is represented by twenty keywords: machine learning, deep learning, gait analysis, neural networks, kinematics, etc. Over the period, the predictive capability of sensors integrated with machine learning and deep learning has become quite useful in detecting irregular organ functions such as heartbeats for saving lives (Sabry et al., 2022). The field of kinematics, the branch of mechanics that causes motion without any applied forces, is another important keyword representing the theme. Many wearable devices are being used to detect the motion of the human body, such as running or physical activities, or performance improvement, especially in sports powered by machine learning methods (Mannini & Sabatini, 2010). The sensors used for kinematics include Inertial measurement units (IMUs) (Sabatini, 2011), a sensor measuring linear acceleration (Yang & Hsu, 2010), a gyroscope – the measurement of the rate of rotation (Muro-de-la-Herran et al., 2014) are commonly used mechanisms.

The blue cluster area represents wearable electronics, covering sensors, health monitoring, wearable devices, flexible electronics, graphene, and smart textiles, including eighteen other keywords. The advancement of wearable devices and wearable technologies, most importantly, their use in health monitoring care, both materials, such as graphene. (Sankar et al., 2020) and sports (Hou & Zuckermann, 2020).

3.8. Thematic Evolution

The thematic evolution analysis shows how a theme of a given field evolved and matured in terms of its wide application. From 1999-2006, the majority of the study focussed on smart clothing, wearable devices, computing, and technology and less on health monitoring, but during 2007-2014, the research was more mature to adopt wearable sensors in health monitoring, activity tracker, clothing was taken over by intelligent textile, and further expansion of subjects such as telemedicine and smartwatches. In 2015-2021, it further matured to focus on wearable technology, wearable devices, and a new domain: wearable electronics (Fig 5). The Concentration of research in the field of wearable devices and technology is under the phase of maturation, and more and more research is dwelling around this field (keywords).

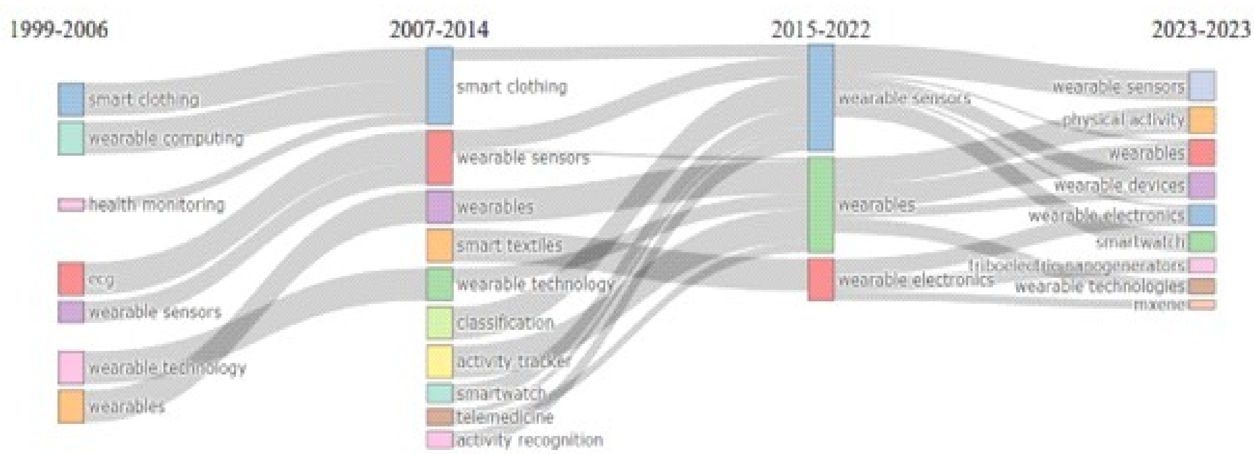

Figure 5. Thematic evolution-based author keywords co-occurrence

4. Discussion

The study's findings unearth the robust and rapidly growing field of research in wearable technology, as reflected by the 7,172 publications from 33,653 authors over 26 years. The results show the multidisciplinary nature of wearable devices, such as engineering, computer science, and medicine.

The high h-index (180), g-index (300), and m-index (6.923) reflected the field influence and weightage. Many highly cited papers indicate that wearable technology is not only a topic of significant academic interest but also one with substantial practical applications. The findings are supported by other studies, such as Ometov et al. (2021), which highlighted the broad application of wearable technologies in various domains, including health monitoring and fitness tracking. The document types include journal articles (49.02%) and conference papers (34.89%), which show dominance and that the field is research-intensive and rapidly evolving, often requiring the dissemination of findings through conferences for timely discussion and feedback. This trend is supported by Sabry et al. (2022), who noted that wearable technology, particularly in healthcare, is driven by continuous innovation and the need for up-to-date research to guide practical applications.

The thematic analysis presented a timeline view and reflected that wearable technology's focus has evolved. Early research (1999-2006) was focused on smart clothing and computing technology. The evolution is reflected in the current emphasis on machine learning and deep learning in wearable devices, as highlighted by recent studies (Nandi et al., 2022). Keyword cluster analysis presents a realistic trend. Keywords such as "health monitoring," "wearable sensors," and "smart textiles" in the network visualization indicate a growing interest in the material science aspects of wearables, such as the use of graphene for flexible electronics (Sankar et al., 2020). Publication trends analysis shows an exponential growth in research output since 2012, with significant peaks in 2019 and 2020. This growth is likely due to advancements in sensor technology and the growing application of wearable devices in health monitoring, as Muro-de-la-Herran et al. (2014) suggested.

Country contribution revealed that the United States is the most prolific country regarding the number of publications and citations, followed by China and the United Kingdom. This may indicate the strong research infrastructure and investment in wearable technology in these countries. The Ministry of Education of the People's Republic of China and the Chinese Academy of Sciences further highlight the strategic focus on this technology in Asia.

5. Conclusion

The bibliometric analysis on wearable devices based on 7172 publications has been carried out for twenty-six years. It shows an incremental research trend and research interest in the domain. The high citations and essential metrics portray a vibrant and impactful research field around wearable devices. The high citation rates, collaborative authorship, and strong presence of influential papers are indications of increasing interest in the field. Most of the publications fall under technology, along with Engineering, Computer Science, and Medicine, which is proof of interdisciplinary research in the field. Since 2012, there has been exponential growth in publications showing research on technical evolution is quite a sought-after domain. This impact can be evident due to enhanced research domains, especially in computer science, sports, and medicine. Most publications appeared in joint authorship, showing collaborative research in the domain. Most authors have been active for a long time and are still contributing to the domain. Notably, most Chinese institutions contribute to wearable device research, whereas the Ministry of Education of the People's Republic of China has contributed the most papers. The United States is the most productive country, whereas publications from South Korea are the most influential, with high average citations per paper. The wearable devices were published in different sources, including journals, conferences, book chapters, and books. Notably, conference papers are significantly high, indicating that the researcher is interested in disseminating their work through presentations at different conferences and seminars. The emerging theme and research hotspots centre on wearable devices, technology, smart textiles, and health monitoring. Over the period, advancements in wearable sensors have been seen as future research opportunities. This study presented an overall bibliometric perspective on wearable device research trends using keywords available in the title field of the database. A systematic approach may be adopted using other fields as well by adhering to the fundamental principle of screening, data cleaning, and refining the data to ensure the relevancy and accuracy of the subject. Future research may be undertaken on the assessment and impact of individual technology in the form of a systematic review or scoping review, which can be assessed to analyse the gaps in research.

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