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QUANTIFYING THE IMPACT OF WEARABLE HEALTH MONITORING AND MACHINE LEARNING RESEARCH: A BIBLIOMETRIC ANALYSIS

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ABSTRACT

Wearable devices that monitor various aspects of an individual's health in real-time are becoming more prevalent. Machine learning algorithms can analyze this medical information resulting in early disease prediction, customized treatment strategies, and enhanced healthcare delivery. Advancements in electronics and machine learning techniques are continuously expanding the potential for developing wearable, miniaturized, and, more particularly, biomedical sensor devices that can integrate sufficient cognitive capacity to analyze captured signals and respond to them. The study focuses on 582 articles published in the Scopus database between 1999 and 2023, highlighting the significant features, including co-authorship, publication patterns, word frequency, co-citation analysis, bibliographic relationships, and much more using VOSviewer and Biblioshiny. Overall, the study's findings provide insights into the current state of research in wearable health monitoring and machine learning and potential recommendations for future research in this rapidly emerging field.

Keywords: *Bibliometric Analysis, Wearable Health Monitoring, Machine Learning, VOSviewer, Biblioshiny.*

1. INTRODUCTION

With the introduction of wearable health monitoring devices and machine learning algorithms, healthcare has undergone tremendous changes in the past few decades [1]. Wearable health-tracking innovations, like smartwatches and fitness bands, measure various physical indicators in real-time, notably blood pressure, pulse, heart rate, emotional states, movement patterns, and sleeping. These devices can potentially revolutionize how we monitor our health and manage chronic conditions by providing personalized, actionable insights. Wearable devices may include numerous sensors, such as temperature, accelerometers, optical, and biometric sensors, that constantly track various health indicators. Although some of these devices' measurements are not as accurate as hospital instruments, they are occasionally regarded as adequate [2],[3].

Machine learning and artificial intelligence constitute essential components in innovative wearable device design [4]-[6]. The two types of Artificial Intelligence and machine learning technology are classical machine learning methodologies [6]. and current deep learning techniques [6],[7]. Classical machine learning techniques include multilayer perceptron (MLP), support vector machines (SVM), decision trees, linear discriminant analysis [6],[8], random forest algorithms [9], Bayesian approaches, and hidden Markov models. Deep learning approaches include convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory (LSTM) networks, deep reinforcement learning, and stacked autoencoder architectures [6],[10],[11]. Wearable health monitoring combined with machine learning has the potential to improve healthcare delivery by changing the emphasis from reactive to proactive and personalized care. This technology can improve medical results, reduce medical expenses, and enable people to take control of their physical well-being.

Bibliometric analysis is a quantitative method for assessing scientific literature that reveals trends and patterns in publication information [12]–[20]. It is a research method that analyzes numerous characteristics of scholarly publications, such as books, articles, and conference papers, intending to get insights into the evolution of studies in an area of study [21–23]. It uses a range of quantitative techniques to evaluate publishing data, such as citation counts, co-authorship, and keyword distribution, in order to spot new emerging trends and patterns [24],[25].

VOSviewer is a potent, straightforward software tool for constructing and visualizing bibliometric networks [26],[27]. Maps and visualizations of bibliometric data are produced using VOSviewer using methods such as co-citation analysis, bibliographic coupling, and co-authorship analysis [26–30]. By highlighting groups of related study topics prominent authors, and prestigious institutions, these maps can help researchers see potential collaborations and novel developments in their fields. Researchers who want to exhibit their bibliographic data in a more captivating and dynamic manner will definitely benefit from Biblioshiny [31]. Using biblioshiny, scholars, and researchers can create versatile and customizable bibliographies which enable quick exploration and analysis of their sources by integrating this package with bibliographic data.

Previous studies have examined various facets of wearable health monitoring and machine learning, contributing valuable insights into their individual advancements. These studies have primarily focused on technical aspects, algorithmic innovations, and clinical applications. While these investigations have provided a deeper understanding of the capabilities and potential of these technologies, they often lack a holistic analysis of the broader research landscape. Previous works have not systematically quantified the cumulative impact, collaborative networks, and evolving trends within this multidisciplinary field.

In contrast, this bibliometric analysis aims to provide a comprehensive overview of the research on wearable health monitoring and machine learning by analyzing the relevant literature published in this field of research. Our motivation lies in unraveling the collective contributions of researchers, institutions, and countries, thereby shedding light on the growth trajectory and intellectual foundations of this dynamic field. The study will examine the research trends, bibliographic coupling, co-authorship of countries, and the collaboration networks of researchers in this field using information obtained from the Scopus database from 1999 to 2023. The study is mainly used to assess the growth and trends along with identifying key authors, institutions, and countries contributing to the field of wearable health monitoring and machine learning research. Also, it quantifies the collaboration networks among researchers and institutions and explores the evolution of research topics, keywords, and themes within the intersection of wearable health monitoring and machine learning. VOSviewer, a bibliometric visualization tool, was used to convey an up-to-date overview of the prevalent research practices. This study does not delve into the technical details of the wearable devices or machine learning algorithms themselves, nor does it address the broader societal, ethical, or clinical implications of these technologies.

2. MATERIALS AND METHODS

The selection of the problem of quantifying the impact of wearable health monitoring and machine learning research is driven by the need to gain a comprehensive understanding of the advancements, trends, and influences in this dynamic field. Through a bibliometric analysis, we aim to contribute to the body of knowledge by providing insights that can guide future research directions, facilitate informed decision-making, and ultimately contribute to the realization of the potential benefits that wearable health monitoring and machine learning technologies can bring to healthcare. The study's scientific papers were sourced from the primary collection of the Scopus database. On May 10, 2023, a search was conducted using the terms "wearable health monitoring" and "machine learning". The search had no language restrictions, and the papers were published between 1999 and 2023. Papers were selected if they were directly related to the intersection of wearable health monitoring and machine learning. Only papers available in peer-reviewed journals and conference proceedings were considered. Non-peer-reviewed articles, workshop papers, and preprints were excluded to ensure the inclusion of high-quality and well-vetted research. The collected data were saved as "CSV" files, including full records and cited reference content. The VOSviewer version 1.6.19 and the Bibloshiny software was used to perform bibliometric analysis on the data. The VOSviewer software tool is obtained for free from https://www.vosviewer.com/. To learn how to use the tool and display overlaid information, refer to a newly published book chapter by Van Eck and Waltman [26], which provides a detailed guide with step-by-step instructions. Additionally, tutorial videos are accessible on the VOSviewer website [26],[32].

Biblioshiny is utilized for visualizing parameters like sources, authors, documents and clustering by coupling. It also enabled us to analyze the conceptual and intellectual structures using data files from various databases.

Figure 1. The Methodology Phases

3. RESULTS

A total of 582 records were found in the Scopus database search. These records include various types of publications such as articles, books, book chapters, conference papers, reviews, and surveys, which were published from 1999 to 2023. The growth in the number of publications was rapid in 1999 and continued until approximately 2005, after which the growth rate became more irregular but remained roughly linear. From 2019 to 2023, the number of publications per year almost reached a plateau. However, the number of publications annually has risen since then. Biblioshiny is utilized to visually represent the connection between the number of published works and the year they were published (Figure 2).

***Figure 2.** The Number of Publications from 1999 to 2023 Represented Using the Tool Biblioshiny.*

3.1 Most Significant Authors

An aggregate of 2122 authors published articles on wearable health monitoring and machine learning research. The number of articles is selected as an indicator and includes authors who published at least ten articles to explore the most prominent authors. Liu J has 13 articles published, followed by Wang Y and Zhang J, having 11 articles. Table 1 shows the number of publications of the most prominent authors, with more than nine publications over time; they all have an extended history of accumulation in their respective domains, giving them supremacy. From 2009 to 2023, Figure 3 illustrates the top nine most productive authors. The volume of articles written by an author in a specific time frame was used to determine productivity.

Table 1. Authors Having More Than Nine Articles

Authors	Articles
Liu J	13
Wang Y	11
Zhang J	11
Li Y	10
Liu Y	10
Wang J	10
Wang X	10
Wang Z	10
Zhang Y	10

Figure 3. Production of Authors Having More Than Nine Articles

3.2 Most Relevant Sources and Affiliations

All 582 publications were gathered from 368 journal sources. Only 18 (4.89%) of the 368 journals have more than four papers. ACS Applied Materials and Interfaces was the most productive journal we examined, with a maximum of 14 articles, followed by the Proceedings of SPIE - The International Society for Optical Engineering, which had 13 publications. The most fruitful 15 journals published papers in Wearable Health Monitoring and Machine Learning research are given in Table 2 and Figure 4 below.

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Figure 4. The Top 15 Relevant Sources in Terms of Number of Publications

Table 2. The Top 15 Relevant Sources in Terms of the Number of Publications

Figure 5 displays the most relevant affiliations from which Wearable Health Monitoring and Machine Learning research publications have been carried out. The Fudan University and the University of California have topped the list with a maximum of 47 publications, followed by Tianjin University with 37. Tsinghua University, Xidian University, and the University of Electronic Science and Technology, China, were the following affiliated institutions where notable research had been performed in this discipline.

Figure 5. Most Relevant Affiliations in Terms of the Number of Publications

3.3 Co-Authorship Network Visualization of Authors

Figure 6 shows the network visualization of co-authorship of researchers publishing on wearable health monitoring and machine learning in the period 1999-2023. Five hundred eighty-two papers were written by 2081 authors, with the number of authors per paper ranging from 5 to 25. Only 45 of the 2081 authors met the thresholds using the full counting method. For each of these 45 writers, their co-authorship links with other writers were examined and the ones with the strongest links were chosen. As a result, 172 total link strengths were found, divided into six clusters containing 36 items. These clusters were named cluster 1, cluster 2, cluster 3, cluster 4, cluster 5, and cluster 6, and contained 8, 8, 7, 6, 5, and 2 items, respectively.

Figure 6. VOSviewer Network Visualization of Researcher Co-Authorship on Wearable Health Monitoring and Machine Learning in 1999-2023.

3.4 Co-Authorship Network Visualization of Countries

Using VOSviewer software, a comprehensive visualization of co-authorship density has been created based on the data. The visualization represents each country with a circle, and the size of the circle represents the number of scientific publications that the country has produced in the field of wearable health monitoring and machine learning. The distance between circles indicates the strength of the co-authorship connection among the countries, with closer circles indicating a powerful connection.

Figure 7 illustrates the visual representation of data from the study on several countries. The data was obtained by counting the number of publications produced by 64 countries, resulting in 582 publications. The number of countries per document varied from a minimum of 5 to a maximum of 25, with 23 countries meeting the required threshold level. The mapping revealed the presence of five clusters, with 23 items in total, distributed among the clusters as follows: cluster 1 (9 items), cluster 2 (4 items), cluster 3 (4 items), clusters 4 and 5 (3 items). The analysis showed that China had the highest total link strength of 34, with 176 articles, followed by the United States, with an absolute link strength of 30 and 134 papers, respectively (Figure 8). In addition, the study demonstrated that China was the leading country in co-authoring papers with other scientists and scholars in wearable health monitoring and machine learning research.

Figure 7. Data Used for Visualizing Co-authorship with Countries in VOSviewer

Figure 8. VOSviewer Density Visualization of the Co-authorship of Countries Publishing on Wearable Health Monitoring and Machine Learning in 1999-2023.

3.5 Bibliographic Coupling with Sources

The visual representation describes a network of bibliographic connections between research articles related to wearable health monitoring and machine learning. Out of 368 sources that published such articles, only 18 met the required criteria, including selecting only those that had published at least five articles and using a full counting method to determine their relevance. This network mapping helps illustrate the connections and interrelationships between research articles and their sources. The total strength of bibliographic coupling links between the 18 sources has been computed. The most significant total link strength (TLS) from their sources was determined and arrived at a value of 3624 TLS, which was then used to group the sources into four clusters comprising 18 items. Specifically, the first two clusters included five items each, while the next two contained four. The data presented indicates that the highest amount of combined link strength achieved was 666, which involved six articles that received a total of 2407 citations from the journal "Advanced Materials", ranking it in the top position. The journal "ACS Applied Materials and Interfaces" followed in second place with 511 combined link strengths from 14 research articles. This suggests that the two journals collaborated significantly in publishing academic papers, as shown in Figure 9 and Figure 10.

Figure 9. Data Used for Visualizing Bibliographic Coupling with Sources in VOSviewer

Figure 10. VOSviewer Network Visualization of the Bibliographic Coupling with Sources on Wearable Health Monitoring and Machine Learning in 1999-2023.

3.6 Bibliographic Coupling with Countries

Figure 11 and Figure 12 displays how bibliographic coupling is associated with different countries in wearable health monitoring and machine learning research. A total of 64 countries took part in publishing academic papers; out of them, 23 countries had more than five publications that were used as the threshold level. Therefore, the table shows six clusters with a total of 23 items, where cluster 1 has eight items, cluster 2 and 3 have four items each, cluster 4 and 5 have three items each, and cluster 6 has only one item. The table also demonstrates the aggregate strength of the bibliographic coupling links between 64 countries and other countries. As per the table, China had the most bibliographic coupling links, which occurred 10,227 times, with 176 documents having 4,565 citations. The United States followed with 8,125 bibliographic coupling links across 134 documents with 6,326 citations. This indicates that both countries heavily relied on each other's research in this field.

Figure 11. Data Used for Visualizing Bibliographic Coupling with Countries in VOSviewer

Figure 12. *VOSviewer Network Visualization of the Bibliographic Coupling with Countries on Wearable Health Monitoring and Machine Learning in 1999-2023.*

3.7 Three Field Plot on Wearable Health Monitoring and Machine Learning

Sankey diagrams are extensively used for depicting the flow of materials in various networks and methods. They use quantifiable characteristics to illustrate flows, linkages, and their transition. Sankey charts are weighed graphs with weight elements that assure flow preservation. The inflow weights at each node are exactly the same as the outflow effects. The processes are visualized using Sankey diagrams, and relationships can be investigated [32]. In Biblioshiny, the three-field plot is used for visualizing the associations among sources of information, countries, affiliations, key phrases, prominent authors, citations, author keywords, and more [33]. Colored rectangles are used for representing essential elements. The rectangle's height represents the association between components like countries, organizations, sources, significant authors, keywords, etc. The wider the rectangle, the more intricate interactions are present among distinct components [33].

Figure 13 depicts an illustration for exploring the relationship between keywords (left), authors (middle), and source (right) in wearable health monitoring and machine learning literary works. The study revealed which keywords in the literature were frequently utilized by various authors and journals published. The top keywords, authors, and sources studied disclosed that there were multiple key phrases such as "wearable health monitoring", "wearable" and "flexible electronics", "health monitoring", "Wearable Sensor", "Sensors" and the top authors Liu Y, Wang H, and Wang J, published in source ACS Applied Materials and Interfaces, and IEEE Sensors Journal.

Figure 13. Three Field Plot Keyword (Left), Author (Middle) and Source (Right) using Biblioshiny.

3.8 Co-Occurrence of Keywords and Content Analysis

A keyword co-occurrence network is constructed by considering every keyword as a node in the network and every co-occurrence of a pair of terms as an association connecting those two phrases. The weight of the link that ties both of these keywords is determined by the number of times a pair of terms co-occur.

Figure 14. Co-occurrence Network Generated by Biblioshiny

Figure 14 presents a word network built on keyword co-occurrence to find meaningful linkages and research themes. Every node in this diagram has been assigned a keyword, and the edge linking pairs of nodes depicts the co-occurrence of keywords. The width of an edge indicates the frequency of co-occurrence of keywords, whereas the size of a node and label represents the frequency of occurrence of a specific keyword. More thickness indicates that the keywords are tightly related. The node's color indicates the cluster with which the phrase is associated. The keywords and linkages between them suggest that each cluster is tied to a research area. The figure shows two distinct clusters that Biblioshiny dynamically recognizes. The greatest cluster is shown in red, and it indicates that the most prominent three terms (such as "wearable sensors," "health monitoring," and "wearable technology") are related to one another. This implies that a significant number of articles have concentrated on the utilization of wearable sensors to monitor health indicators using technological advancements. In addition, these keywords are associated with phrases such as "monitoring", "health", "wearable health monitoring systems", "electrocardiography", "health monitoring devices", and more. The second cluster is depicted in a blue color and comprises keywords like "human", "humans", "electronic device", and "wearable electronic devices".

3.9 Clustering and Coupling of Source Journals

Given a unit count of 250, a minimal cluster frequency per 1,000 units of 10, and a label count of five for each cluster, the coupling map of source journals, determined by references and local citation score, created three clusters (Figure 15). Out of the three clusters, the sources such as ACS Nano Sensors and Actuators, Physical Sensors (Switzerland), IEEE Transactions on biomedical circuits and Systems, and Annual International Conference of the IEEE Engineering in Medicine and Biology – proceedings were in the same cluster (Frequency = 47). The sources like Advanced Materials, Advanced Healthcare Materials, Advanced Functional Materials, Advanced Materials Technologies, and Advanced Materials Interfaces were located in a separate cluster (Frequency = 15). The third cluster (Frequency = 11) is made up of sources such as Medical and biological engineering and computing proceedings, International Conference on Tools with artificial intelligence, ICTAI proceedings – 2021, 3rd International Conference on Advances in Computing, Communication Control, and Networking, ICA3N 2021 journal of medical systems, Studies in health technology and informatics.

Figure 15. Clustering by Source Coupling Measured by References and Local Citation Score.

3.10 Most Frequent Words and Word Cloud of the Authors' Keywords

Figure 16 depicts the most frequently used key phrases and their frequency of occurrence. The top ten keywords were "wearable sensors (182)", "wearable technology (171)", "health monitoring (167)", "wearable health-monitoring systems (138)", "monitoring (122)", "electrocardiography (100)", "health (100)", "human (86)", "health monitoring devices (79)", "humans (78)".

Figure 16. The Most Frequently Used Keywords

The authors' keywords are bound in the word cloud in Figure 17. The goal of employing a word cloud for the articles under consideration is to study the most often occurring phrases, implying that most of the analysis is done in those sectors. A word cloud, turns text input into identifiers, usually short terms whose relative importance is reflected by their color in the resulting cloud. This establishes links between the authors' primary keywords, which are spread around the most significant keywords such as "wearable sensors", "wearable technology", "health monitoring", and so on.

Figure 17. A Visualized Word-cloud of Frequently used Keywords

3.11 Word TreeMap

Indexing tools and search engines use keywords in articles to find pertinent articles. If the search engines can discover the authors' keywords, the work of literature becomes available to users, enhancing the number of citations. These data can be used to identify research trends and possibly exciting areas for further investigation. The articles' top 50 most often used terms are displayed in the word TreeMap. The TreeMap in Figure 18 combines potential keywords in wearable health monitoring and machine learning research. The most popular keyword was health monitoring, while there were several least popular key phrases.

Figure 18. Word Tree Map

3.12 Thematic map

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A thematic map is a two-dimensional representation of typological themes. The analysis of keywords is used to identify keyword clusters, which results in motifs in the research discipline. These themes can be separated into four quadrants on a two-dimensional structure where centrality and density are two distinct dimensions. A bubble can identify each theme on the graph (Figure 19). The key phrases mentioned the most frequently were human, humans, and electronic device, and they had the most excellent density and centrality in the upper right quadrant of the map. Wearable sensors, wearable technology, and health monitoring were central themes in the lower right quadrant, suggesting critical but unexplored areas. The upper left quadrant highlighted niche themes such as electrodes, flexible electronics, and pressure sensors, which had undergone extensive development yet had poor external linkages. Wearable health monitoring systems, monitoring, and health were insufficiently developed, highlighting growing and diminishing ties.

Figure 19. Thematic Map

3.13 Conceptual Structure Map using Multiple Correspondence Analysis

Bibliometrix utilizes network analysis, correspondence analysis (CA), and multiple correspondence analysis (MCA) to investigate phrases from article titles, abstracts, and keywords. CA and MCA depict the conceptual structure in two distinct planes [34]. In this scenario, multiple correspondence analysis is used to construct a framework of the discipline to identify clusters of articles that convey similar ideas, and the findings are projected on a two-dimensional network. MCA's conceptual structure map includes all the keywords while accounting for network homogeneity [34].

Figure 20 depicts the classification of common keywords into two groups. Cluster 1 (blues) covered wearable technology, health monitoring systems, electrodes, wearable sensors, biosensors, diagnosis, etc. Cluster 2 (red) covered algorithms, equipment design, devices, and heart rate.

Figure 20. Structure Map Developed from the Multiple Correspondence Analysis.

4. DISCUSSION

In the Scopus database search, 582 records were discovered that were released from 1999 to 2023. The number of publications increased from 1999 to 2005 but became more erratic, yet followed a general linear trend. The annual publication count reached a plateau from 2019 to 2023 but raised in the following years. The rate of increase per year is approximately 14.06%, and the typical number of references for each document is 26.12.

Prominent authors in wearable health monitoring and machine learning research, such as Liu J, Wang Y, and Zhang J, have contributed significantly with multiple published articles. A small fraction of journals provides the majority of publications, with ACS Applied Materials and Interfaces leading in production, followed by Proceedings of SPIE - The International Society for Optical Engineering. Fudan University and the University of California are the most prominent institutions in Wearable Health Monitoring and Machine Learning research, with Tianjin University close behind.

The co-authorship network of researchers publishing on wearable health monitoring and machine learning is extensive, with 2081 authors contributing to 582 papers over 24 years. However, only a small number of authors (45) met the specified thresholds, indicating that only a few are highly connected within the network. Furthermore, the 172 link strengths found were divided into six clusters, each containing varying items, which suggests that the network is not evenly distributed and has distinct subgroups. These findings could be used to understand the network structure better and identify key players within it.

China is the leading country in co-authoring papers on wearable health monitoring and machine learning research, with the highest total link strength of 34 and 176 articles produced. The United States follows with an absolute link strength of 30 and 134 papers. The findings also revealed five clusters of countries based on the overall number of publications. A total of 23 countries met the given threshold value. According to the results, researchers collaborate tremendously in wearable health monitoring and machine learning, with China playing a pivotal part.

The graphical depiction of bibliographic linkages between research papers shows the interconnections between various literature sources and articles. The aggregate strength of bibliographic coupling links among every source has been estimated, and this data was then utilized to divide the sources into four clusters depending on cumulative link strength. The data presented also shows that the journal "Advanced Materials" had the highest combined link strength, indicating that it has played a significant role in publishing and disseminating research articles in this field. Furthermore, the close collaboration between "Advanced Materials" and "ACS Applied Materials and Interfaces" suggests that these two journals are essential players in the research community for wearable health monitoring and machine learning.

China and the United States are the leading countries in wearable health monitoring and machine learning research, as evidenced by the high number of bibliographic coupling links between them. Furthermore, these two countries heavily relied on each other's research in this field, which indicates a strong collaboration between them. Moreover, the data shows six clusters of countries based on their bibliographic coupling, with China and the United States likely being in different clusters due to their high levels of collaboration. Finally, the fact that 64 countries participated in publishing academic papers in this field suggests that wearable health monitoring and machine learning research are active and vital areas of study worldwide.

The study explored the association between keywords, authors, and sources from diverse literary sources, identifying the most commonly used keywords, authors who contributed considerably, and the sources where those works have been released. As a result, several important terms have been discovered, including "wearable health monitoring", "wearable", and "flexible electronics", "health monitoring", "Wearable Sensor", and "Sensors". Liu Y, Wang H, and Wang J were the most notable authors using these key phrases, with work published in ACS Applied Materials and Interfaces and IEEE Sensors Journal.

The co-occurrence network showcases two distinct clusters, with the larger red cluster focusing on wearable sensors, health monitoring, and wearable technology. In contrast, the blue cluster relates to humans and wearable electronic devices. This analysis suggests that a significant body of research has concentrated on utilizing wearable sensors to monitor health indicators, with technological advancements playing a crucial role in this area of study. The coupling map of source journals generated three clusters that grouped the primary sources according to references and local citation scores.

Based on the frequently occurring keywords and the authors' essential keywords, the study strongly emphasizes wearable sensors, wearable technology, and health monitoring. The thematic map analysis reveals distinct keyword clusters in four quadrants, with human-related keywords dominating the upper right quadrant, wearable technology and health monitoring in the lower right quadrant, niche themes with poor external linkages in the upper left quadrant, and insufficiently developed wearable health monitoring systems in a state of fluctuation.

The network analysis and multiple correspondence analysis performed by Bibliometrix reveal multiple clusters of articles based on their keywords, with Cluster 1 emphasizing wearable technology and health monitoring systems and Cluster 2 focusing on algorithms, equipment design, devices, and heart rate.

5. LIMITATIONS

A possible drawback involves depending solely on the Scopus database, which might lead to the omission of pertinent research from alternative databases. Furthermore, the analysis could be prone to biases due to the selection of specific keywords and search phrases.

6. CONCLUSION

The bibliometric study of "Wearable Health Monitoring and Machine Learning" conveys valuable insights into scientific analysis advancements and patterns in this discipline. According to the findings, there has been considerable growth in the amount of publications in this field, revealing an increasing fascination with wearable health monitoring and its possible applications in healthcare services. Researchers have primarily focused on designing wearable gadgets capable of measuring numerous health indicators and using machine learning algorithms to improve the accuracy and precision of the data acquired. Furthermore, disease diagnosis and prediction, vital sign monitoring, and activity recognition are among this sector's most popular research areas. In addition, the study identified many noteworthy authors and countries that have made significant contributions to wearable health monitoring and machine learning research. China and the United States stand out as pivotal contributors, leading the co-authorship landscape with a significant total link strength and substantial article production. The analysis of bibliographic coupling links highlighted the significance of journals like "Advanced Materials" and "ACS Applied Materials and Interfaces" in disseminating research. Finally, the bibliometric study gives light on the current state of wearable health monitoring and machine learning research. The study's findings can assist researchers and practitioners in identifying critical areas of focus and potential collaborations for future research endeavors.

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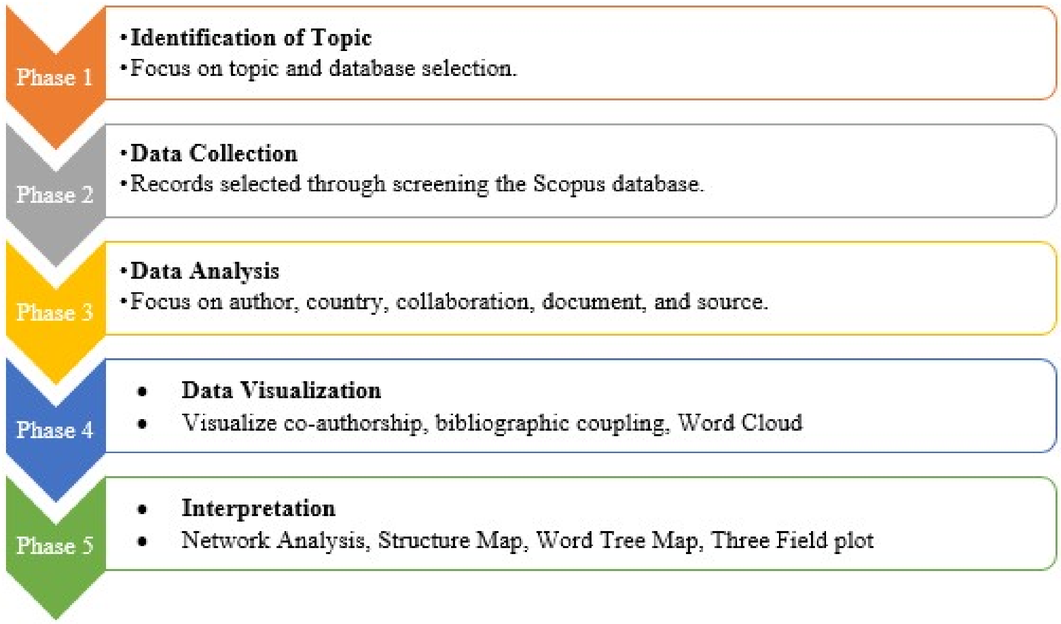

Figure 1. The Methodology Phases

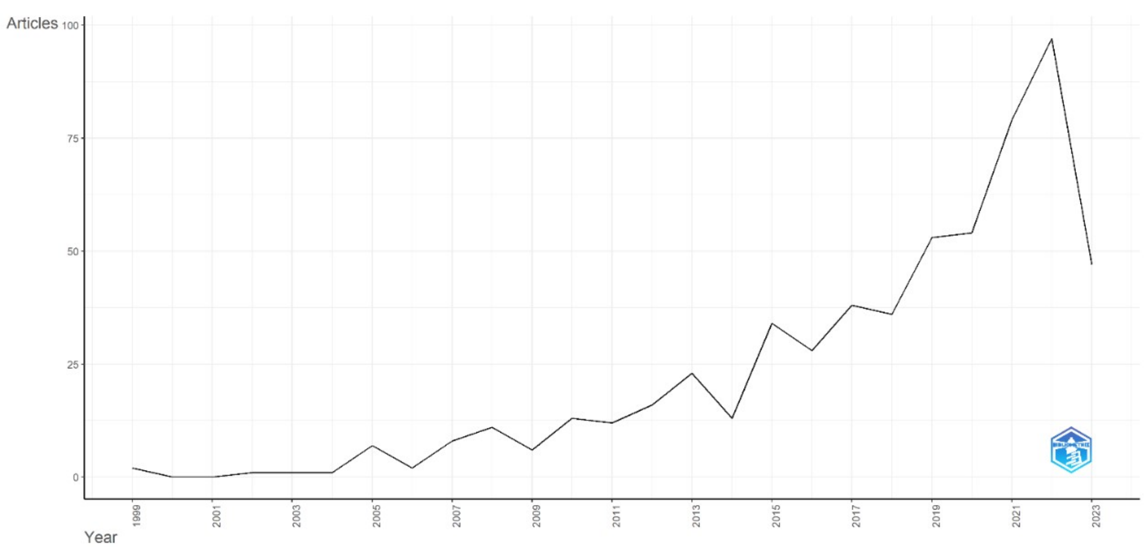

Figure 2. *The Number of Publications from 1999 to 2023 Represented Using the Tool Biblioshiny.*

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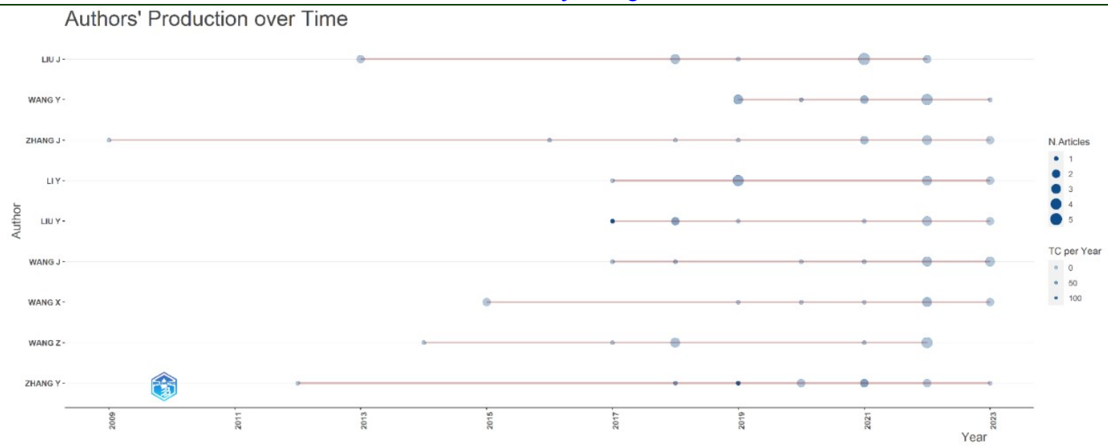

Figure 3. Production of Authors Having More Than Nine Articles

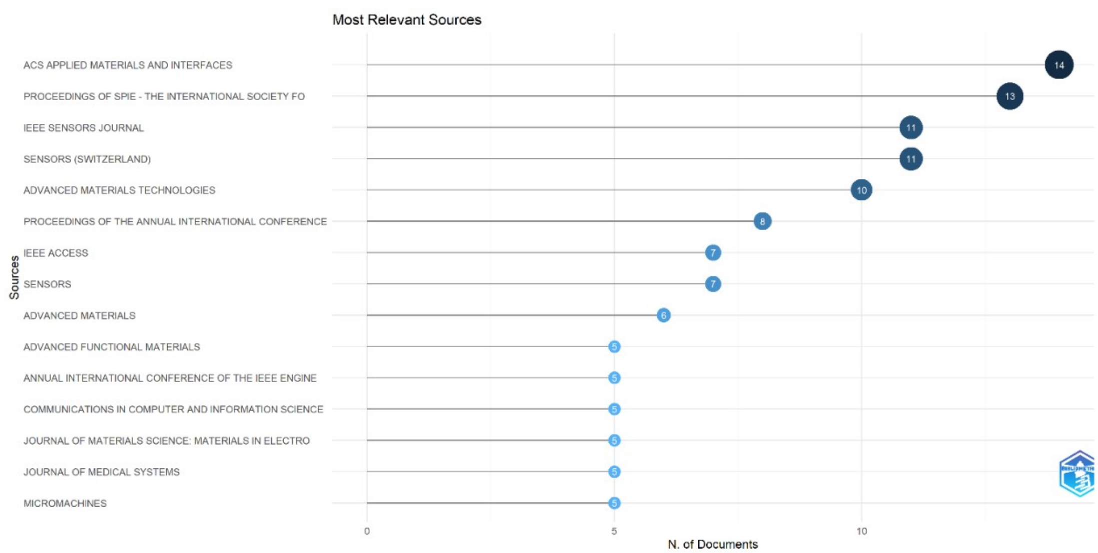

Figure 4. The Top 15 Relevant Sources in Terms of Number of Publications

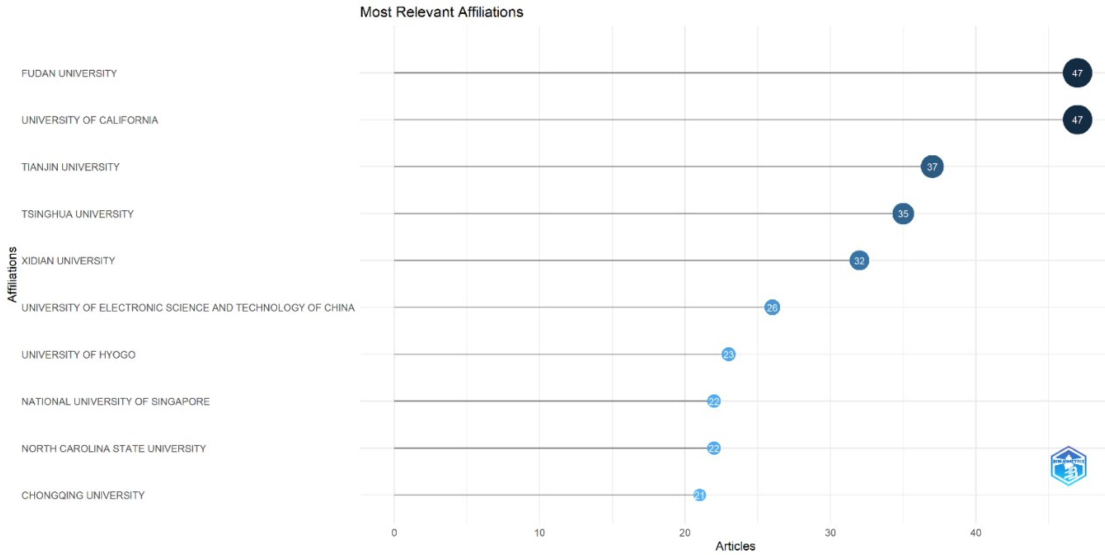

Figure 5. Most Relevant Affiliations in Terms of the Number of Publications

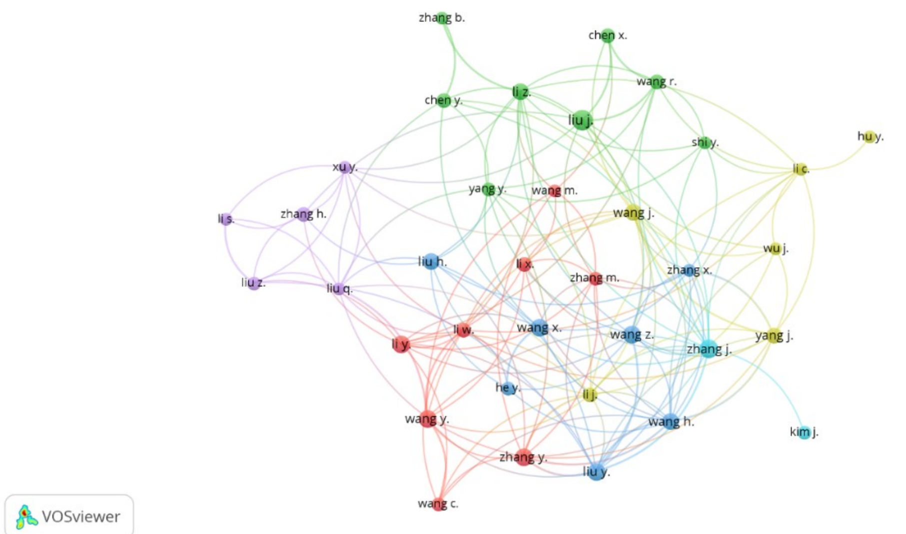

Figure 6. VOSviewer Network Visualization of Researcher Co-Authorship on Wearable Health Monitoring and Machine Learning in 1999-2023.

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Country	Documents	Citations	Total link strength
china	176	4565	34
united states	134	6326	30
india	62	579	11
south korea	41	967	11
germany	15	376	9
saudi arabia	8	392	8
belgium	7	293	7
hong kong	10	107	7
pakistan	5	187	7
united kingdom	23	590	7
italy	8	216	6
singapore	12	382	6
france	14	173	5
australia	11	197	4
bangladesh	5	81	4
portugal	8	164	4
finland	7	40	3
japan	28	556	3
malaysia	10	272	3
switzerland	7	1222	3

Figure 7. Data Used for Visualizing Co-Authorship with Countries in VOSviewer

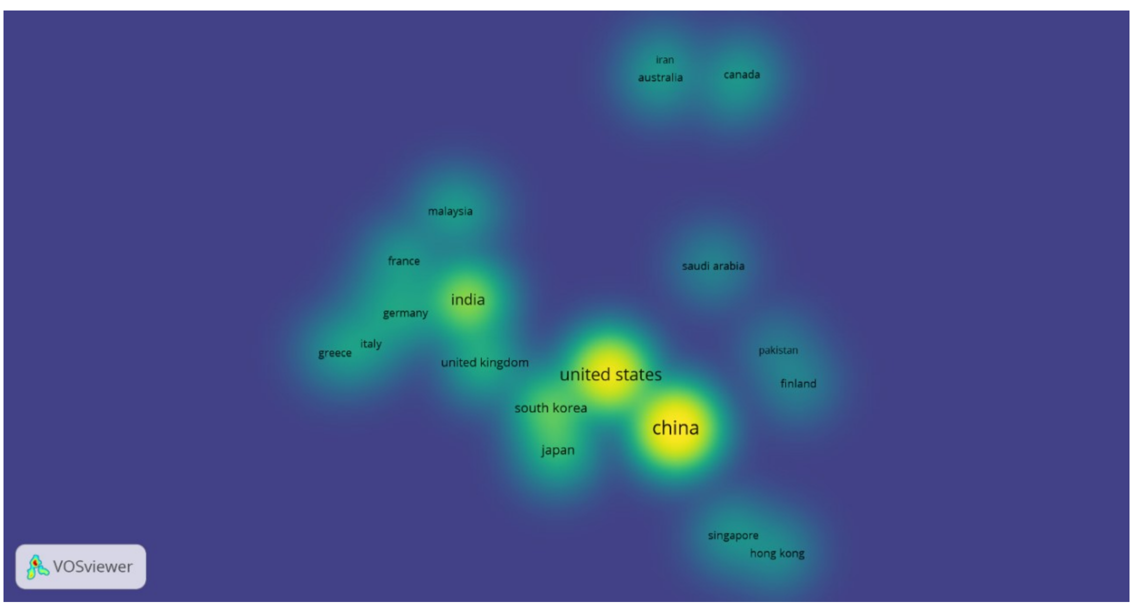

Figure 8. VOSviewer Density Visualization of the Co-Authorship of Countries Publishing on Wearable Health Monitoring and Machine Learning in 1999-2023.

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Source	Documents	Citations	Total link strength
advanced materials	6	2407	666
acs applied materials and interfaces	14	636	511
advanced materials technologies	10	299	509
sensors	7	41	397
sensors (switzerland)	11	529	340
advanced functional materials	5	537	282
micromachines	5	40	182
nano energy	5	133	149
ieee sensors journal	11	72	145
proceedings of spie - the international society for optical engineering	13	96	144
scientific reports	5	340	123
journal of materials science: materials in electronics	5	67	70
ieee access	7	123	50
journal of medical systems	5	361	19
proceedings of the annual international conference of the ieee engin...	8	65	17
annual international conference of the ieee engineering in medicine ...	5	163	12
communications in computer and information science	5	3	6
wireless communications and mobile computing	5	34	2

Figure 9. Data Used for Visualizing Bibliographic Coupling with Sources in VOSviewer

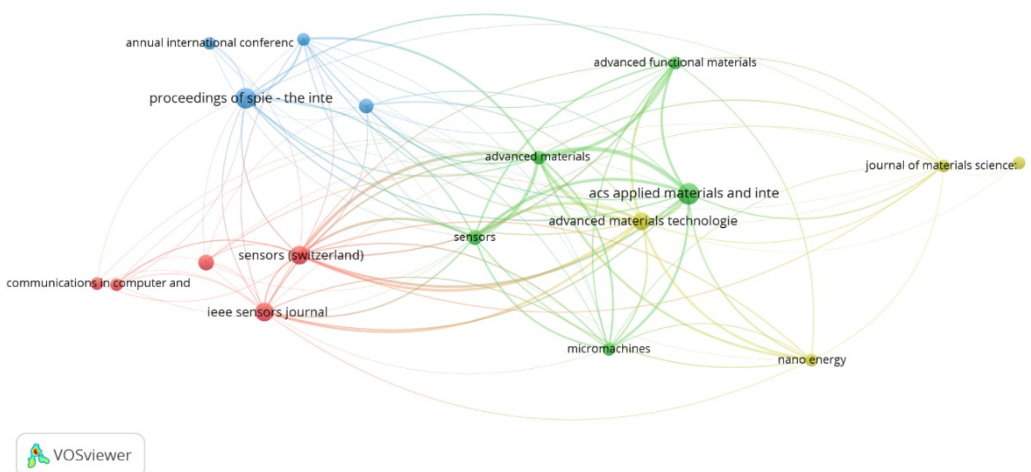

Figure 10. VOSviewer Network Visualization of the Bibliographic Coupling with Sources on Wearable Health Monitoring and Machine Learning in 1999-2023.

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Country	Documents	Citations	Total link strength
china	176	4565	10227
united states	134	6326	8125
south korea	41	967	3086
japan	28	556	1904
india	62	579	1859
singapore	12	382	1463
united kingdom	23	590	1433
bangladesh	5	81	949
switzerland	7	1222	948
iran	5	73	862
hong kong	10	107	856
germany	15	376	741
australia	11	197	688
saudi arabia	8	392	683
malaysia	10	272	593
canada	11	154	520
portugal	8	164	516
france	14	173	473
belgium	7	293	428
italy	8	216	426

Figure 11. Data used for Visualizing Bibliographic Coupling with Countries in VOSviewer

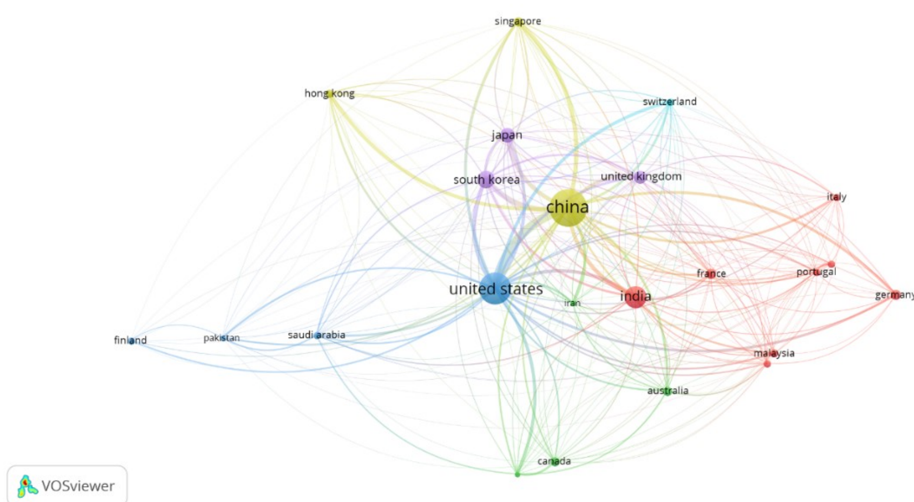

Figure 12. *VOSviewer Network Visualization of the Bibliographic Coupling with Countries on Wearable Health Monitoring and Machine Learning in 1999-2023.*

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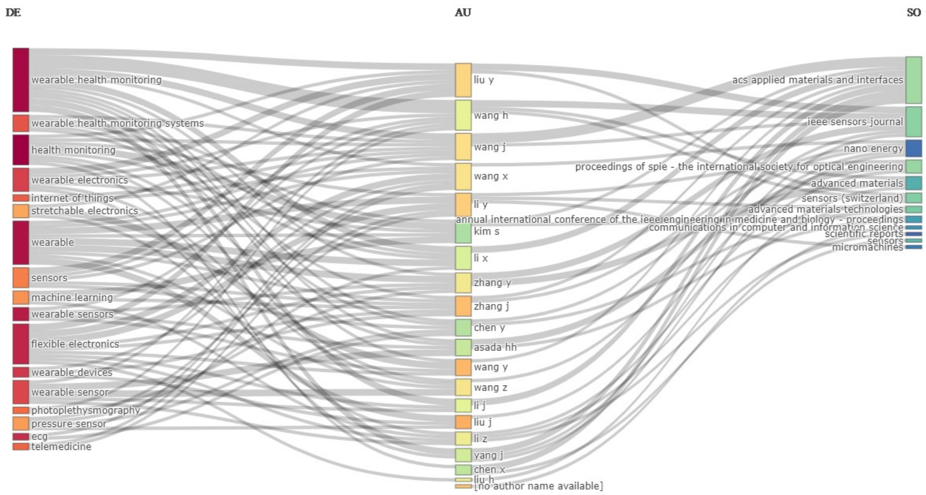

Figure 13. Three Field Plot Keyword (Left), Author (Middle) and Source (Right) using Biblioshiny.

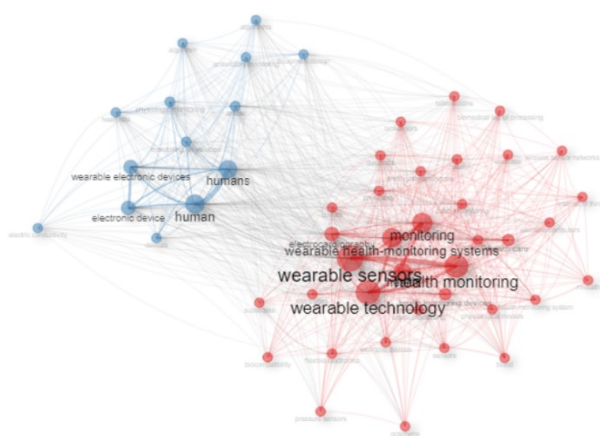

Figure 14. Co-occurrence Network Generated by Biblioshiny

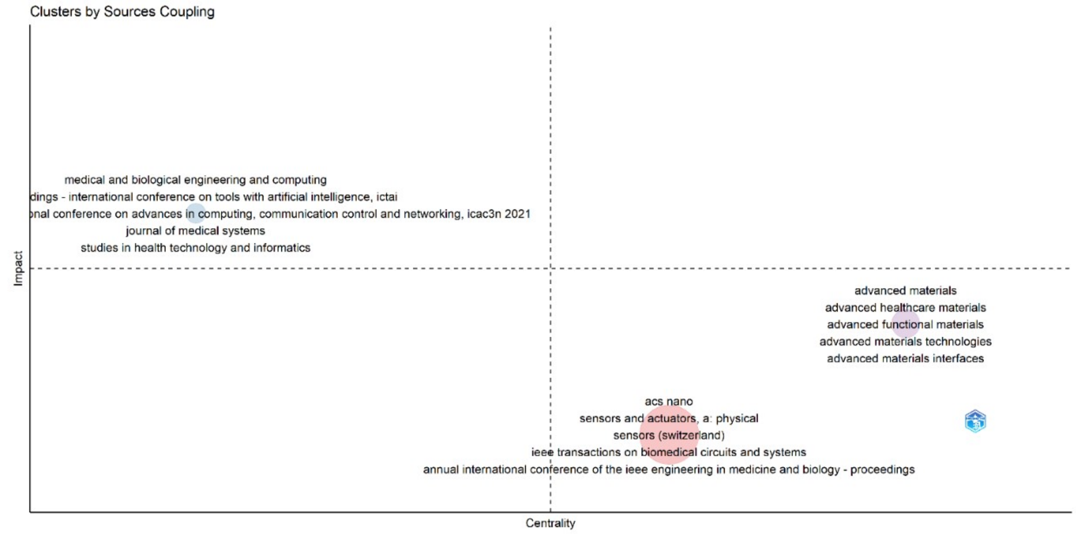

Figure 15. Clustering by Source Coupling Measured by References and Local Citation Score.

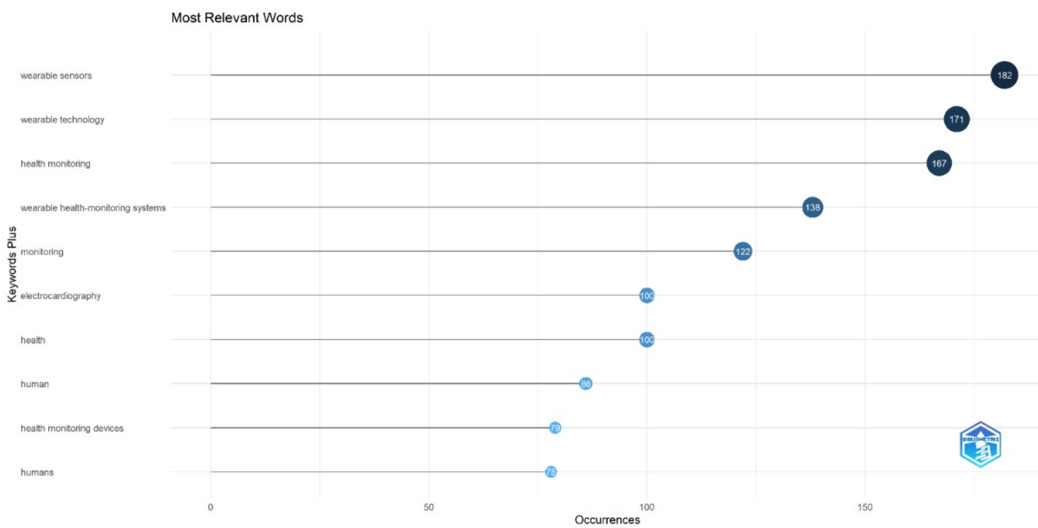

Figure 16. The Most Frequently Used Keywords

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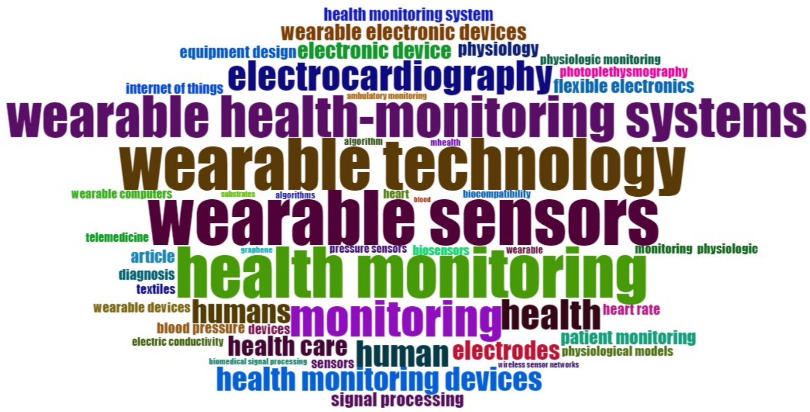

Figure 17. A Visualized Word-cloud of Frequently Used Keywords

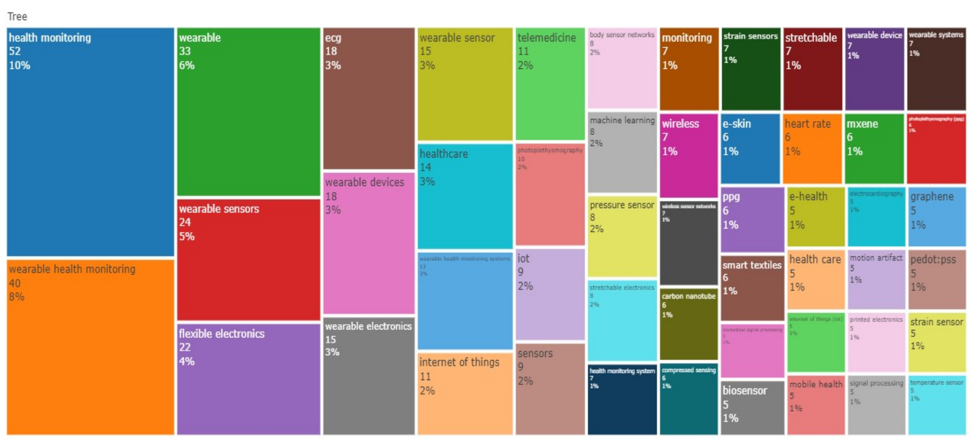

Figure 18. Word Tree Map

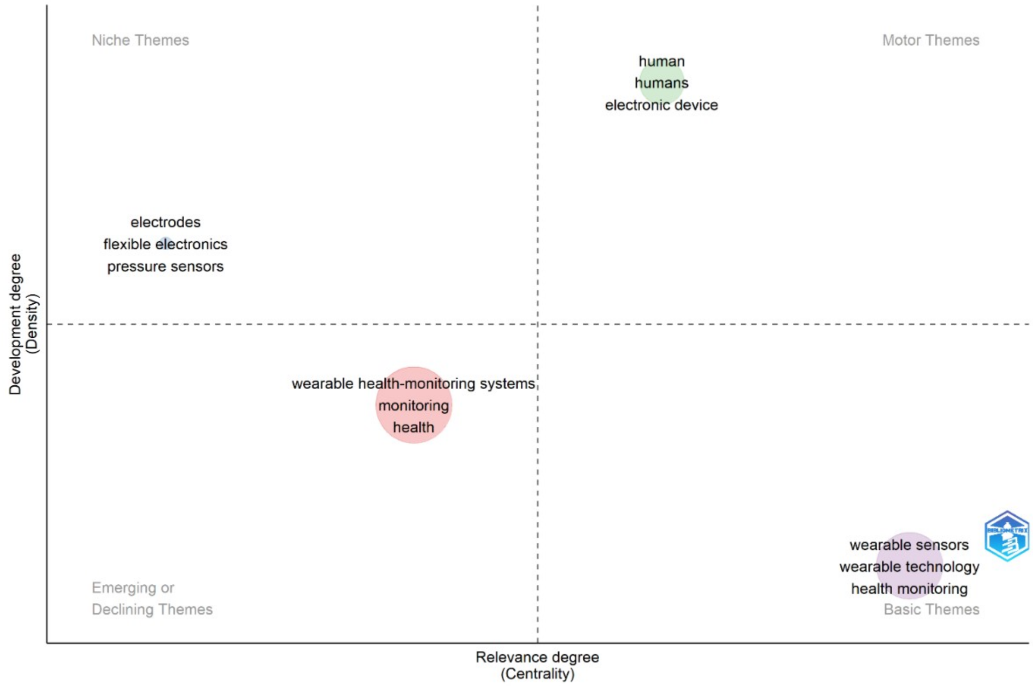

Figure 19. Thematic Map

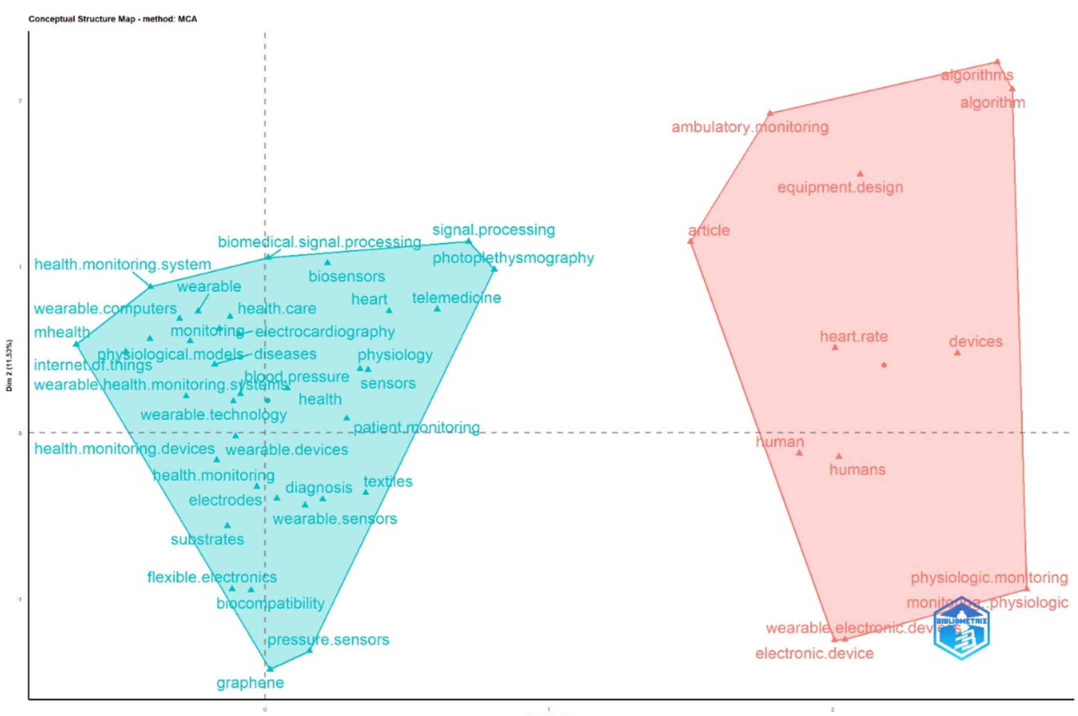

Figure 20. Structure Map Developed from the Multiple Correspondence Analysis.

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Table 2. The Top 15 Relevant Sources in Terms of the Number of Publications

Sources	Articles
ACS Applied Materials and Interfaces	14
Proceedings of SPIE - The International Society for Optical Engineering	13
IEEE Sensors Journal	11
Sensors (Switzerland)	11
Advanced Materials Technologies	10
Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS	8
IEEE Access	7
Sensors	7
Advanced Materials	6
Advanced Functional Materials	5
Annual International Conference of the IEEE Engineering in Medicine and Biology – Proceedings	5
Communications in Computer and Information Science	5
Journal of Materials Science: Materials in Electronics	5
Journal of Medical Systems	5
Micro machines	5
Nano Energy	5
Scientific Reports	5
Wireless Communications and Mobile Computing	5
ACM International Conference Proceeding Series	4
Advanced Healthcare Materials	4
Advanced Materials Interfaces	4
Advances in Intelligent Systems and Computing	4
IEEE Transactions on Biomedical Circuits and Systems	4
Lecture Notes in Computer Science (Including subseries lecture notes in Artificial Intelligence and lecture notes in Bioinformatics)	4
Nanoscale	4