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Bibliometric Analysis of Research on Digital Medicine in Cardiovascular Diseases from 2004 to 2022

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ABSTRACT

This study aims to provide a comprehensive overview of research on digital medicine in cardiovascular diseases (CVD), exploring its evolution, knowledge framework, and current research hotspots, and offering insights for future investigations in this field. Publications from January 2004 to October 2022 were collected from the Web of Science Core Collection (WoSCC). CiteSpace was utilized to visualize keyword trends, co-citation networks, and emerging research frontiers, while VOSviewer mapped the contributions of authors, institutions, and countries, integrating their link strengths into the analysis.

A total of 5,265 English-language articles were included. Publication output has steadily grown each year. The United States led in the number of publications, followed by England. Harvard Medical School was the most prolific institution, with Massachusetts General Hospital and Brigham and Women's Hospital also ranking highly. The journal JMIR mHealth and uHealth was the most influential outlet. Among authors, Noseworthy PA stood out for both citation counts and total link strength. The application of wearable devices in CVD—covering risk identification, diagnosis, preventive strategies, early intervention, and remote management—emerges as a foundational and highly explored area. Future research directions may include evaluating the clinical impact of digital interventions on chronic disease management, applying machine learning (ML) for atrial fibrillation (AF) detection and early risk assessment, and developing predictive models for CVD outcomes using neural networks (NNs), ML, and unsupervised learning approaches. Research on digital medicine in CVD has grown markedly in recent years. This bibliometric study presents a detailed map of the field, serving as a reference for researchers aiming to advance knowledge and practice in this area.

Keywords: Digital medicine, Review, Cardiovascular diseases, VOSviewer, Knowledge-map, CiteSpace

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Introduction

Cardiovascular diseases (CVD) remain the leading chronic non-communicable health threat globally [1], with prevalence and mortality rates rising and affecting increasingly younger populations [2]. Beyond the severe health consequences, CVD imposes substantial social and economic burdens.

Digital medicine, leveraging mobile technologies and wearable devices, offers novel opportunities for early detection, diagnosis, intervention, remote monitoring, and long-term management of CVD [3]. Significant progress has been achieved in this field, particularly during the COVID-19 pandemic [4]. Examples of these applications include AI-enabled electrocardiogram analysis (AI-ECG) for early identification of left atrial myopathy [5], detection of atrial fibrillation (AF) during sinus rhythm [6–10], concealed long QT syndrome [7, 11], aortic valve stenosis [12], asymptomatic left ventricular dysfunction (ALVD) [13, 14], left ventricular systolic dysfunction [15–17], patients with low ejection fraction [18], Graves disease-associated AF, heart failure with reduced ejection fraction [19], hyperkalemia [20], and home blood pressure–driven remote hypertension management [21–23].

Digital interventions—including smartphone apps and text messaging—have demonstrated potential in improving lifestyle behaviors [15, 20, 24–27], controlling cardiovascular risk factors [25], and supporting tele-rehabilitation programs [28], ultimately enhancing the quality of life and physical functioning in patients with heart failure (HF) [20, 24, 29–33]. Despite the growing evidence, there remains a lack of systematic reports summarizing research trends, key institutions and scholars, highly influential studies, and emerging hotspots in digital medicine applied to CVD.

Bibliometric analysis provides a structured approach for quantifying and evaluating research output, allowing detailed exploration of authorship, keywords, journals, countries, institutions, and references within a field [34, 35]. This study employs bibliometric and visualization techniques to systematically summarize digital medicine research in CVD from January 2004 to October 2022, highlighting current trends and potential directions for future research.

Materials and Methods

Data collection

All publications were retrieved from the Web of Science Core Collection (WoSCC) on October 15, 2022, with data collected in a single day to avoid inconsistencies caused by daily updates. The search strategy was:

(TS = ((Digital medicine) OR (Digital health) OR (Digital therapeutics) OR (Digital interventions) OR (Medical software programs) OR Apps OR Smartphone OR Mobile OR telehealth OR e-Cardiology OR (Digital cardiology) OR (Artificial Intelligence))) AND (TS = ((Cardiovascular Disease) OR (Coronary Disease) OR (Coronary Heart Disease) OR Hypertension OR (Arrhythmias, Cardiac) OR (Atrial Fibrillation) OR (Heart Failure) OR (Myocardial Bridging))).

The inclusion period ranged from January 1, 2004, to October 15, 2022, and only articles were included. Search results were exported as plain text files, with "Full Record and Cited References" selected, and saved as download_.txt*.

Data analysis and visualization

CiteSpace was used to identify co-citation networks, keyword trends, and emerging research fronts. The exported download_.txt* file was imported, duplicates removed, and the analysis period set from 2004 to 2022. The top 50 keywords and co-cited references per time slice were selected (Top N = 50). Network pruning was applied as needed using Pathfinder Network (PFNET), Minimum Spanning Tree (MST), or no pruning. Synonyms (e.g., "Heart failure" and "Heart failure disease") were merged, and irrelevant terms were excluded.

VOSviewer was also employed to visualize the distribution of publications by country, institution, and author [36], using full counting and incorporating link strength into the analysis tables. Journal impact factors (IF) and 2022 Journal Citation Reports (JCR) were obtained from WoS, and H-index and global ranking metrics were included for a more comprehensive scientometric assessment. The workflow of this bibliometric study is illustrated in **Figure 1**.

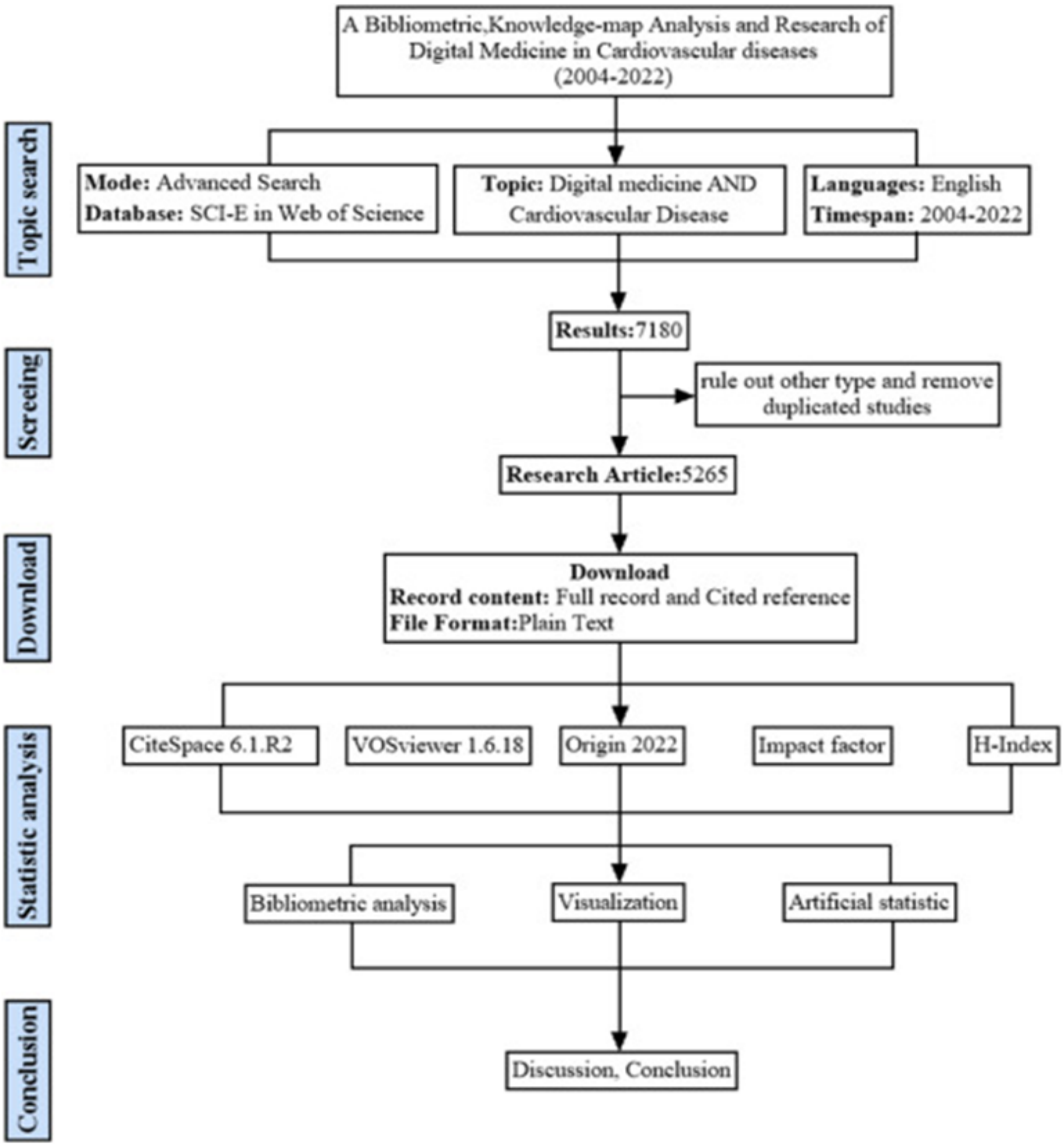


Figure 1. Flow diagram of the bibliometric analysis process. SCI-E = Science Citation Index Expanded.

Results and Discussion

Annual publication trends

By October 15, 2022, a total of 5,265 articles on digital medicine in CVD had been identified. Annual publication counts provide insight into the development and relevance of a research field, and these trends are illustrated using histograms and line charts **(Figure 2)**. Over the past two decades, the number of publications has steadily increased, reflecting growing scholarly interest in this area. Between 2004 and 2014, annual publications rose nearly fourfold, from 55 to 229. From 2017 onward, this growth accelerated, with yearly outputs increasing from 321 to 865, representing an annual growth of approximately 22–33%. Based on this trajectory, it is estimated that publications in 2022 would be roughly 30% higher than in the previous year.

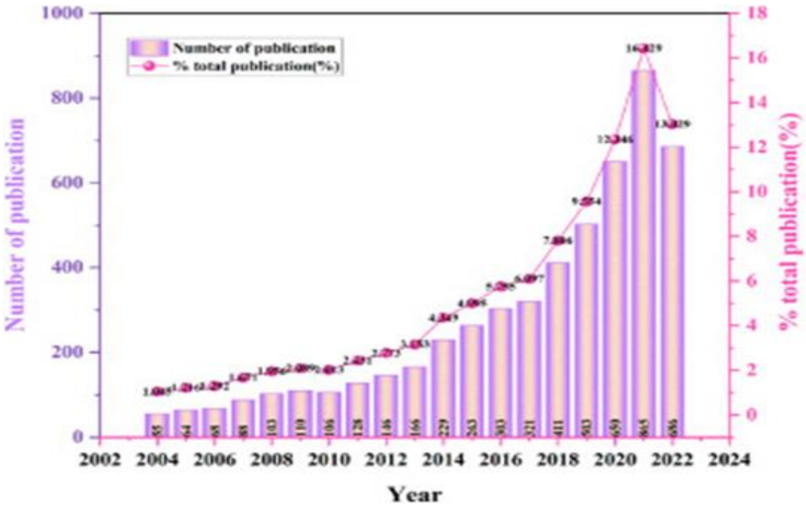


Figure 2. Number and percentage of annual publications on digital medicine in CVD from 2004 to 2022.

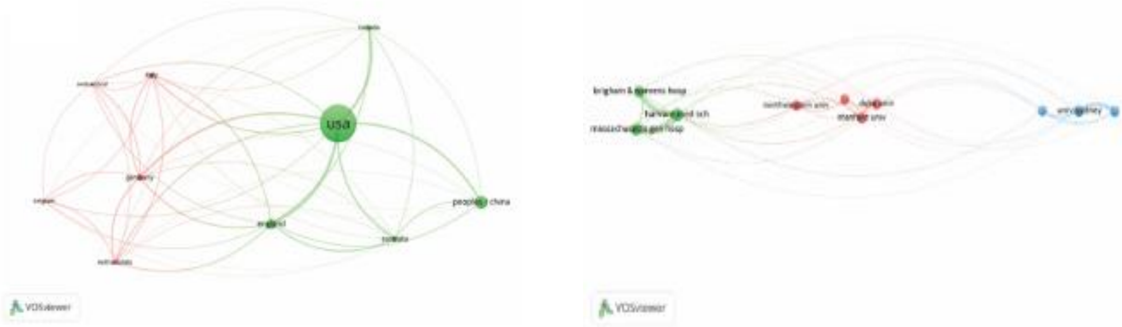
Distribution of countries/regions and institutions

To assess the contributions of various countries and institutions and to identify potential collaborations among them, VOSviewer was employed to generate co-occurrence maps for countries **(Figure 3a)** and institutions **(Figure 3b)**. The top 10 countries and institutions in terms of publication output, along with their total link strength, are presented in **Table 1**. Researchers from approximately 100 countries/territories contributed to the 5,265 articles analyzed. The United States, England, Germany, the Netherlands, and Italy emerged as the most prolific countries, with the US leading by publishing 1,843 articles, highlighting its pivotal role in digital medicine research within the CVD domain.

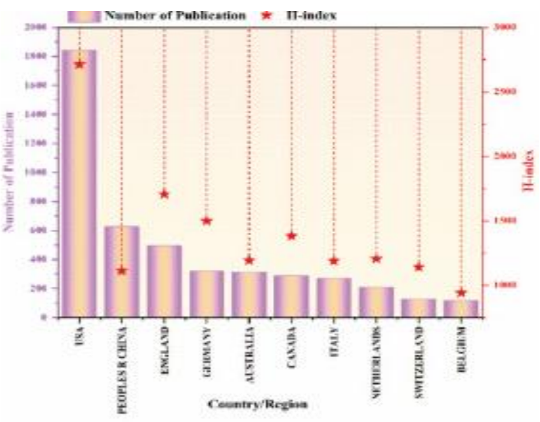
Among the leading 10 institutions, seven were based in the United States, reflecting the country's substantial share of total publications. Total link strength serves as an indicator of collaborative activity, and the US exhibited a link strength approximately 32% higher than England, the second-ranking country, demonstrating its extensive international cooperation and dominant contributions. Harvard Medical School, Massachusetts General Hospital, and Brigham and Women's Hospital were the top three institutions. Harvard Medical School slightly surpassed the other two in total link strength, suggesting a stronger collaborative approach. Notably, Brigham and Women's Hospital, ranked third, is affiliated with Harvard Medical School, further underscoring Harvard's significant influence in this research area.

Some institutions, including the University of Sydney, Duke University, and Oxford University, displayed relatively low total link strength but contributed substantially to publications, indicating that contribution and collaborative intensity are not always directly proportional. Less prominent institutions or countries may still exhibit strong collaborative intentions.

The H-index and global ranking **(Figures 3c and 3d)** are reliable indicators of scientific impact and are commonly used to evaluate academic influence [37, 38]. Combining country and institutional data, the United States achieved an H-index of 2,711 and hosts multiple internationally renowned institutions, confirming its leading position in digital medicine research for CVD. Other notable contributors include England (1,707), Germany (1,498), and the Netherlands (1,206), all of which have made significant contributions to the field.



a) b)



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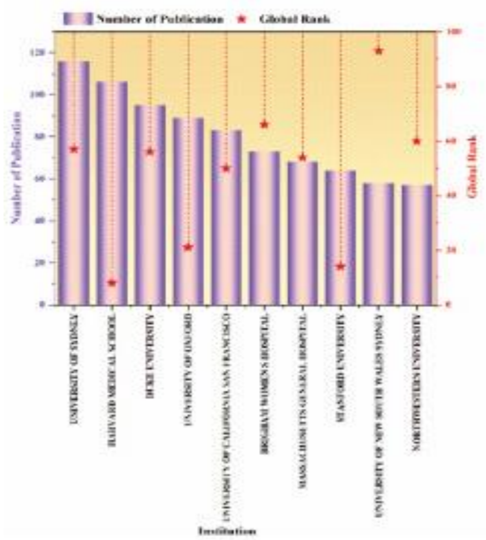


d)

Figure 3. Analysis of contributing countries/regions and institutions. (a) Network map of countries/regions involved in the research. (b) Network map of participating institutions. (c) Publication counts and H-index scores of countries/regions. (d) Publication counts of institutions and their global rankings. In panels A and B, larger nodes represent greater contributions by a country or institution, while the thickness of the connecting lines reflects the strength of collaboration between nodes—the thicker the line, the closer the cooperative relationship.

Table 1. Top 10 countries and institutions contributed to the publications

Rank	Institution	Frequency/Total link strength (Institution)	Global Rank	Country	Frequency/Total link strength (Country)	H-index
1	Harvard Medical School	106/64	8	USA	1843/604	2711
2	Massachusetts General Hospital	68/48	54	England	494/458	1707
3	Brigham Women's Hospital	73/36	66	Germany	321/353	1498
4	University of Sydney	116/33	57	Netherlands	209/270	1206
5	Duke University	95/27	56	Italy	271/265	1189
6	University of New South Wales	58/27	93	Canada	287/260	1381
7	Stanford University	64/26	14	Australia	314/257	1193
8	Northwestern University	57/23	60	China	627/215	1112
9	University of California, San Francisco	83/20	50	Switzerland	126/204	1142
10	University of Oxford	89/20	21	Belgium	117/178	942

Distribution of journals and authors

A total of 1,481 journals published articles in this field, with over 29,520 authors contributing to the 5,265 publications analyzed. The top ten journals are presented in **Table 2**, four of which are based in the United States. JMIR mHealth and uHealth led in publication output with 149 articles (2.83%), followed by Journal of Medical Internet Research with 141 articles (2.68%) and Telemedicine and e-Health with 108 articles (2.05%).

To explore potential collaborations among researchers, a co-authorship network was generated using VOSviewer. **Figure 4** illustrates the author network, while **Table 3** highlights the top 10 most productive authors along with their total link strength. In this network, Noseworthy PA was the most prominent author, contributing 30 articles (0.57%) and achieving the highest total link strength of 111, reflecting extensive collaboration with other researchers. In contrast, Freedman B displayed a considerably lower total link strength, indicating a tendency to conduct research more independently.

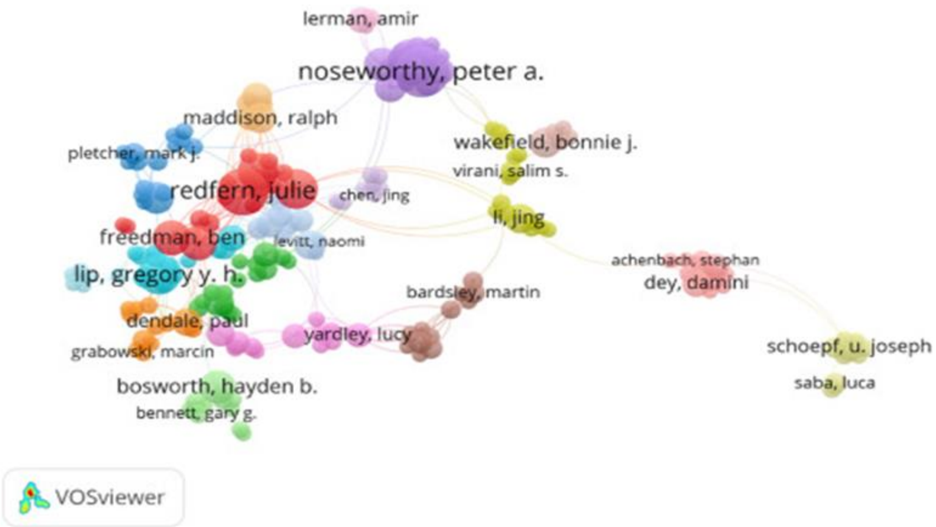


Figure 4. Co-authorship network of researchers contributing to digital medicine studies in CVD from 2004 to 2022.

Table 2. Top 10 journals with the most published articles (N = 5265)

Rank	Country affiliation	Journal	IF 2022 / JCR 2022	Frequency (%)
1	Canada	JMIR mHealth and uHealth	4.947 / Q1	149 (2.830 %)
2	Canada	Journal of Medical Internet Research	7.076 / Q1	141 (2.678 %)
3	United States	Telemedicine and e-Health	5.033 / Q1	108 (2.051 %)
4	United Kingdom	BMJ Open	3.006 / Q2	107 (2.032 %)
5	United States	PLoS One	3.752 / Q2	81 (1.538 %)
6	United Kingdom	Journal of Telemedicine and Telecare	6.344 / Q1	64 (1.216 %)
7	United Kingdom	BMC Public Health	4.135 / Q2	55 (1.045 %)
8	Netherlands	Journal of Chromatography B: Analytical Technologies in the Biomedical and Life Sciences	3.318 / Q2	50 (0.950 %)
9	United Kingdom	Trials	2.728 / Q4	50 (0.950 %)
10	Switzerland	Frontiers in Cardiovascular Medicine	5.846 / Q2	49 (0.931 %)

Table 3. Top 10 most active authors (N = 5265)

Rank	Author	Total link strength	Frequency (%)
1	Noseworthy PA	67	30 (0.570 %)
2	Redfern, Julie	42	27 (0.513 %)
3	Friedman, Paul A	68	26 (0.494 %)
4	Chow, Clara K	34	21 (0.399 %)
5	Lip, Gregory Y. H.	0	21 (0.399 %)
6	Thiagarajan, Aravinda	29	19 (0.361 %)
7	Neubeck, Lis	23	17 (0.323 %)
8	Cafazzo, Joseph A.	21	17 (0.323 %)
9	Freedman, Ben	11	17 (0.323 %)
10	Lopez-Jimenez, Francisco	45	16 (0.304 %)

Distribution of co-cited references and citation bursts

Co-citation refers to the phenomenon in which two publications are cited together by subsequent studies. **Table**

4 lists the top 10 co-cited references, each cited at least 26 times. The most frequently co-cited work in the context of digital medicine for CVD was “Screening for cardiac contractile dysfunction using an artificial intelligence-enabled electrocardiogram” by Attia Z, published in Nature Medicine [13]. The second most co-cited reference was the guideline “2016 ESC Guidelines for the diagnosis and treatment of acute and chronic heart failure” by Ponikowski P, published in European Heart Journal [39]. Notably, half of the top 10 co-cited papers focused on the use of smart devices or screening tools for arrhythmia detection, including studies on AI-ECG algorithms, smartwatches for atrial fibrillation identification, remote heart rhythm monitoring with the AliveCor device, and deep neural network–based arrhythmia classification [13, 40–43].

Cluster analysis, a statistical approach to categorize data based on similarity, was applied to uncover the structure of research topics within this domain [13, 44]. The quality of clustering was evaluated using modularity (Q) and silhouette (S) scores, where $Q > 0.3$ indicates meaningful structural division, $S > 0.5$ suggests reasonable clustering, and $S > 0.7$ denotes robust and reliable clusters. Using CiteSpace, keyword co-occurrence and clustering were performed. The resulting network **(Figure 5)** comprised 1,002 nodes and 3,390 links (density = 0.0068), achieving $Q = 0.7831$ and $S = 0.9099$, indicating a highly structured and reliable clustering outcome. Eleven clusters were identified, with the nine largest labeled in the figure.

The largest cluster (#0, 128 members, silhouette = 0.907) was labeled artificial intelligence. The second (#1, 103 members, silhouette = 0.849) was physical activity, followed by the third (#2, 93 members, silhouette = 0.867) labeled systems demonstrator telehealth questionnaire. Cluster #3 (86 members, silhouette = 0.88) was labeled nurse guidance, cluster #4 (84 members, silhouette = 0.797) as hypertension management, and cluster #5 (65 members, silhouette = 0.902) as atrial fibrillation. Cluster #6 (63 members, silhouette = 0.972) represented elderly people, cluster #7 (41 members, silhouette = 0.955) was evident II, and cluster #8 (24 members, silhouette = 0.973) was labeled cryptogenic stroke.

Citation burst analysis, performed using CiteSpace, identified 20 references experiencing significant surges in citations. The earliest burst began in 2009 with Clark RA *et al.*’s study “Telemonitoring or structured telephone support programs for patients with chronic HF: systematic review and meta-analysis” published in BMJ [45]. Among all references, Ponikowski P *et al.*’s 2016 ESC guideline [39] exhibited the strongest citation burst, with a burst strength of 12.97, highlighting its major influence on the field.

Table 4. Top 10 co-cited references in the research

Rank	Author(s)	Year	Frequency	Source	Co-cited reference (shortened title + DOI)
1	Attia Z	2019	46	Nat Med	Screening for cardiac contractile dysfunction using an AI-enabled ECG (10.1038/s41591-018-0240-2)
2	Ponikowski P	2016	43	Eur Heart J	2016 ESC Guidelines for the diagnosis and treatment of acute and chronic heart failure (10.1093/eurheartj/ehw128)
3	Perez M	2019	41	New Engl J Med	Large-Scale Assessment of a Smartwatch to Identify Atrial Fibrillation (10.1056/NEJMoa1901183)
4	Attia Z	2019	41	Lancet	AI-enabled ECG algorithm for identifying AF during sinus rhythm (10.1016/S0140-6736(19)31721-0)
5	Halcox J	2017	38	Circulation	REHEARSE-AF Study: Remote Heart Rhythm Sampling Using AliveCor to Screen for AF (10.1161/CIRCULATIONAHA.117.030583)
6	Hannun A	2019	37	Nat Med	Cardiologist-level arrhythmia detection with deep neural network (10.1038/s41591-018-0268-3)
7	Burke L	2015	36	Circulation	Current Science on Consumer Use of mHealth for CVD Prevention – AHA Statement (10.1161/CIR.0000000000000232)
8	Johnson K	2018	31	J Am Coll Cardiol	Artificial Intelligence in Cardiology (10.1016/j.jacc.2018.03.521)
9	Benjamin E	2019	30	Circulation	Heart Disease and Stroke Statistics-2019 Update – AHA Report (10.1161/CIR.0000000000000659)
10	Chow C	2015	26	JAMA	Effect of Lifestyle-Focused Text Messaging on Risk Factor Modification in CHD Patients (10.1001/jama.2015.10945)

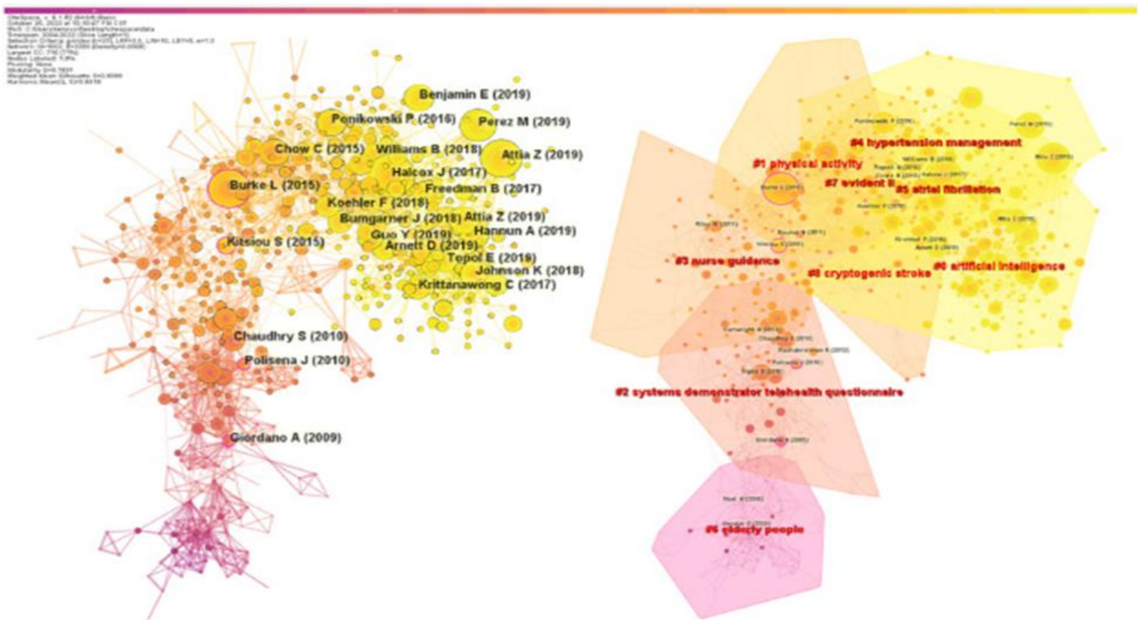
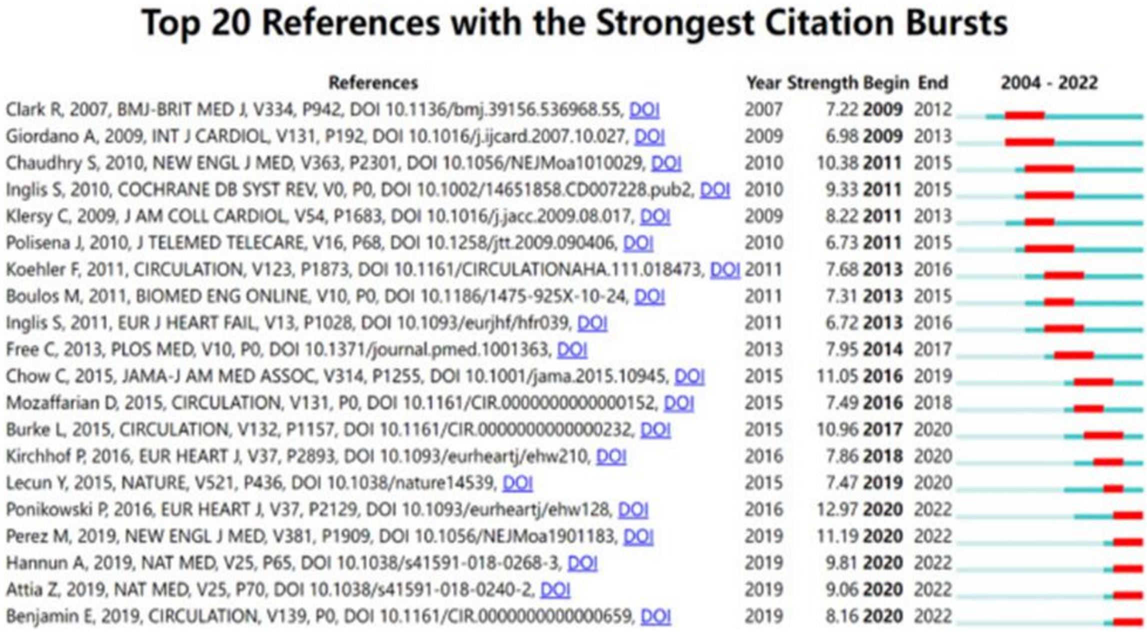


Figure 5. Co-citation network analysis of references from publications on digital medicine in CVD between 2004 and 2022.



Top 20 References with the Strongest Citation Bursts

References	Year	Strength	Begin	End	2004 - 2022
Clark R, 2007, BMJ-BRIT MED J, V334, P942, DOI 10.1136/bmj.39156.536968.55, DOI	2007	7.22	**2009**	2012	
Giordano A, 2009, INT J CARDIOL, V131, P192, DOI 10.1016/j.ijcard.2007.10.027, DOI	2009	6.98	**2009**	2013	
Chaudhry S, 2010, NEW ENGL J MED, V363, P2301, DOI 10.1056/NEJMoa1010029, DOI	2010	10.38	**2011**	2015	
Inglis S, 2010, COCHRANE DB SYST REV, V0, P0, DOI 10.1002/14651858.CD007228.pub2, DOI	2010	9.33	**2011**	2015	
Klersy C, 2009, J AM COLL CARDIOL, V54, P1683, DOI 10.1016/j.jacc.2009.08.017, DOI	2009	8.22	**2011**	2013	
Polisena J, 2010, J TELEMED TELECARE, V16, P68, DOI 10.1258/jtt.2009.090406, DOI	2010	6.73	**2011**	2015	
Koehler F, 2011, CIRCULATION, V123, P1873, DOI 10.1161/CIRCULATIONAHA.111.018473, DOI	2011	7.68	**2013**	2016	
Boulos M, 2011, BIOMED ENG ONLINE, V10, P0, DOI 10.1186/1475-925X-10-24, DOI	2011	7.31	**2013**	2015	
Inglis S, 2011, EUR J HEART FAIL, V13, P1028, DOI 10.1093/eurjhf/hfr039, DOI	2011	6.72	**2013**	2016	
Free C, 2013, PLOS MED, V10, P0, DOI 10.1371/journal.pmed.1001363, DOI	2013	7.95	**2014**	2017	
Chow C, 2015, JAMA-J AM MED ASSOC, V314, P1255, DOI 10.1001/jama.2015.10945, DOI	2015	11.05	**2016**	2019	
Mozaffarian D, 2015, CIRCULATION, V131, P0, DOI 10.1161/CIR.0000000000000152, DOI	2015	7.49	**2016**	2018	
Burke L, 2015, CIRCULATION, V132, P1157, DOI 10.1161/CIR.0000000000000232, DOI	2015	10.96	**2017**	2020	
Kirchhof P, 2016, EUR HEART J, V37, P2893, DOI 10.1093/eurheartj/ehw210, DOI	2016	7.86	**2018**	2020	
Lecun Y, 2015, NATURE, V521, P436, DOI 10.1038/nature14539, DOI	2015	7.47	**2019**	2020	
Ponikowski P, 2016, EUR HEART J, V37, P2129, DOI 10.1093/eurheartj/ehw128, DOI	2016	12.97	**2020**	2022	
Perez M, 2019, NEW ENGL J MED, V381, P1909, DOI 10.1056/NEJMoa1901183, DOI	2019	11.19	**2020**	2022	
Hannun A, 2019, NAT MED, V25, P65, DOI 10.1038/s41591-018-0268-3, DOI	2019	9.81	**2020**	2022	
Attia Z, 2019, NAT MED, V25, P70, DOI 10.1038/s41591-018-0240-2, DOI	2019	9.06	**2020**	2022	
Benjamin E, 2019, CIRCULATION, V139, P0, DOI 10.1161/CIR.0000000000000659, DOI	2019	8.16	**2020**	2022	

Figure 6. Top 20 references exhibiting the strongest citation bursts.

Keyword co-occurrence, clustering, and burst analysis

A keyword co-occurrence network was generated using CiteSpace to explore research focus and trends in digital medicine for CVD **(Figure 7)**. Among the collected data, 42 keywords appeared more than 25 times. **Table 5** summarizes the top 20 most frequent terms. Central topics included heart failure (515 occurrences), artificial intelligence (399), hypertension (379), atrial fibrillation (359), mobile health (215), and physical activity (170). Several keywords, such as cardiovascular disease, management, intervention, mortality, risk factor, association, and mobile health, acted as bridges connecting different areas of research.

The unpruned co-occurrence and clustering network consisted of 42 nodes and 52 links, with a density of 0.0604, Q = 0.7128, and S = 0.919, demonstrating strong and reliable clustering. Six primary clusters were identified and labeled as follows:

- Cluster #0 – "heart failure": Included 8 keywords such as myocardial infarction, digital subtraction angiography, adherence, diagnosis, outcome, care, impact, and management.

- Cluster #1 – "cardiovascular disease": Included 7 keywords: digital health, coronary heart disease, prevention, mortality, health, blood pressure, and risk.
- Cluster #2 – "risk factor": 8 keywords including performance liquid chromatography, population, human plasma, validation, prevalence, hypertension, disease, and risk factor.
- Cluster #3 – "artificial intelligence": 7 keywords such as stroke, classification, coronary artery disease, deep learning, machine learning, mobile health, and atrial fibrillation.
- Cluster #4 – "physical activity": 5 keywords including quality of life, mobile phone, randomized controlled trial, meta-analysis, and intervention.
- Cluster #5 – "association": 2 keywords, guideline and adult.

The timeline visualization **(Figure 8)** traced the evolution of research hotspots over time. During 2004–2011, studies focused on acute myocardial infarction, chronic HF, hypertension, atrial fibrillation, digital subtraction angiography, performance, quantification, and quality of life. From 2012 onward, attention shifted to technological innovations and digital tools, including telemedicine, telehealth, big data, primary care, wearable devices, mobile and smartphone applications, echocardiography, chronic disease management, and mental health. Keyword burst detection, which identifies sudden surges in term usage over time, revealed emerging research trends. The top 20 keywords with bursts are shown in **Table 6 and Figure 9**. The green line represents the full study period (2004–2022), while red segments indicate periods of intense focus. Since 2017, the most prominent bursts include guideline (2018–2019, strength 21.88), impact (2018–2019, strength 7.96), classification (2020–2022, strength 19.45), digital health (2020–2022, strength 15.85), cardiovascular artery diseases (2020–2022, strength 15.18), and diagnosis (2020–2022, strength 11.82), highlighting current priorities in the field.

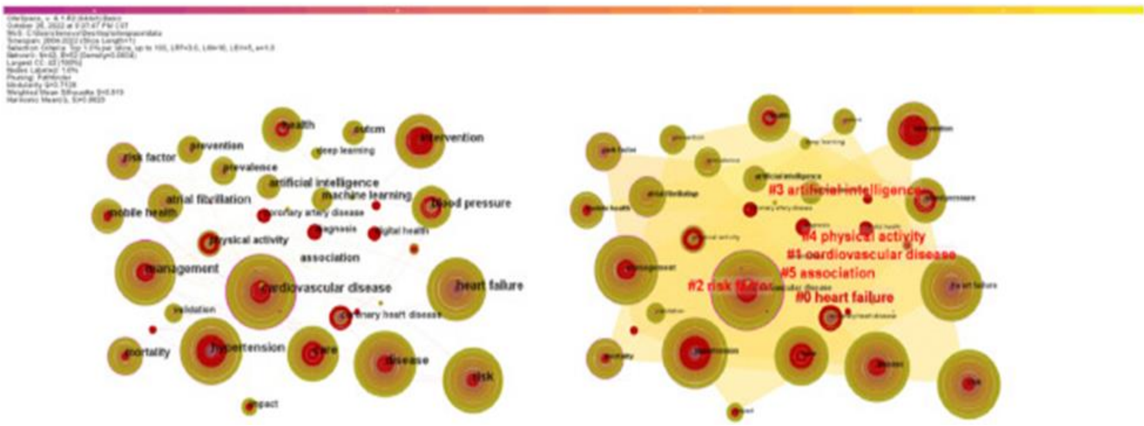


Figure 7. Keyword analysis of research on digital medicine in CVD from 2004 to 2022, where larger crosses indicate higher keyword frequency.

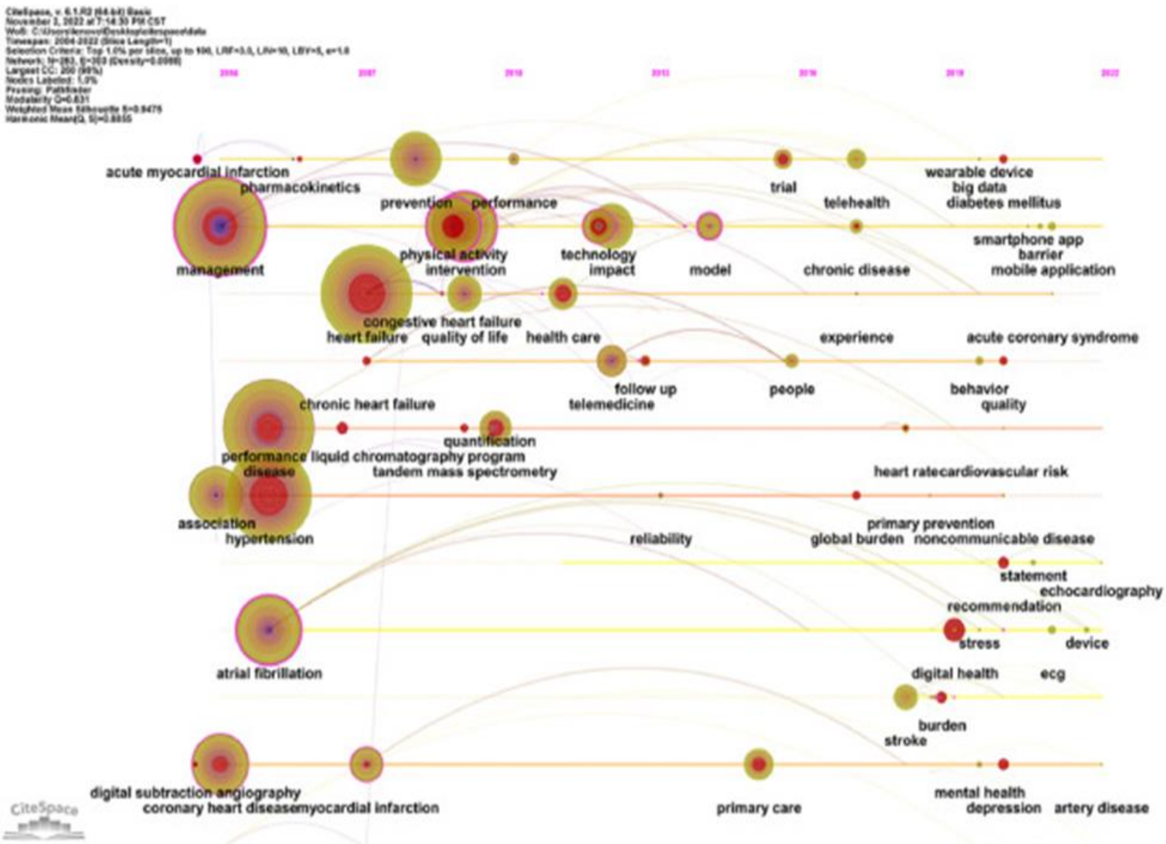


Figure 8. Timeline view of keywords in digital medicine research for CVD from 2004 to 2022.

Table 5. Top 10 co-cited references in the research

Rank	Keyword	Frequency	Centrality
1	cardiovascular disease	639	1.45
2	management	515	0.86
3	heart failure	515	0.19
4	risk	506	0.09
5	disease	448	0
6	artificial intelligence	399	0.38
7	hypertension	379	0.28
8	care	378	0
9	atrial fibrillation	359	0.52
10	intervention	313	0.21
11	blood pressure	310	0
12	health	287	0.09
13	mortality	239	0.68
14	risk factor	232	0.61
15	mobile health	215	0.58
16	machine learning	213	0
17	association	210	0.1
18	physical activity	170	0.36
19	prevalence	168	0

20	prevention	160	0

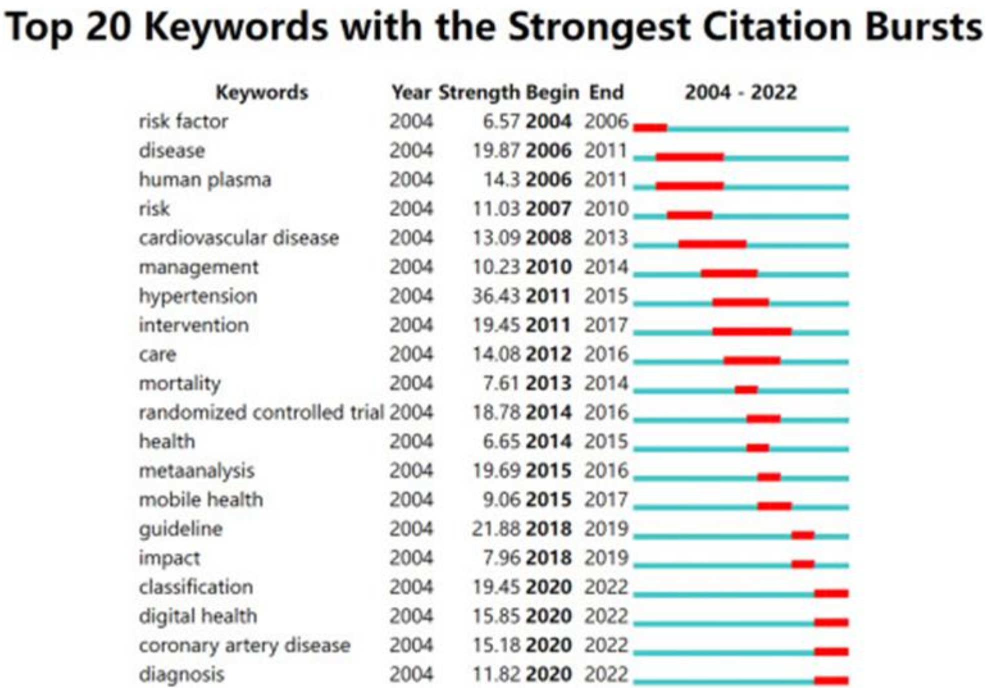


Figure 9. The top 20 keywords exhibiting citation bursts, arranged by the year each burst began.

Table 6. Top 20 keywords with the strongest citation bursts (lasting until 2022)

Keyword	Begin Year	Strength
risk factor	2004	6.57
disease	2006	19.87
human plasma	2006	14.30
risk	2007	11.03
cardiovascular disease	2008	13.09
management	2010	10.23
hypertension	2011	36.43
intervention	2011	19.45
care	2012	14.08
mortality	2013	7.61
randomized controlled trial	2014	18.78
health	2014	6.65
meta analysis	2015	19.69
mobile health	2015	9.06
guideline	2018	21.88
impact	2018	7.96
classification	2020	19.45
digital health	2020	15.85
coronary artery disease	2020	15.18
diagnosis	2020	11.82

Knowledge base of digital medicine in CVD

The early work of Baldassarre D. *et al*. evaluated the potential of artificial neural networks (ANN) to identify individuals with or without a prior history of vascular events by analyzing vascular risk factors, carotid ultrasound measurements, or a combination of both. Their findings highlighted the promise of ANN as a tool for developing precise diagnostic methods to detect patients at high risk for CVD [46]. Over the past twenty years, publications in digital medicine for CVD have steadily increased, with particularly rapid growth observed in the last five years, reflecting the field's expanding importance. A total of 5,265 articles from the Web of Science Core Collection (WoSCC) between January 2004 and October 2022 were included in this analysis, and publications in the first ten months of 2022 alone accounted for nearly 30% of the total output over the previous five years **(Figure 2)**, underscoring the rising prominence and research interest in this area.

Analysis of countries and institutions revealed that nine out of the top ten most productive countries are developed nations, with China as the only developing country, indicating that leadership in this field is concentrated in the United States, the United Kingdom, and other developed regions. China's research in digital medicine started relatively later, with the National Medical Products Administration (NMPA) approving its first digital therapy product in November 2020. Nevertheless, the high prevalence of chronic CVDs such as coronary heart disease, hypertension, and heart failure in China, combined with the country's strong mobile internet infrastructure, presents substantial opportunities for digital medicine interventions focused on lifestyle management. These factors highlight the need for enhanced international collaboration to accelerate development and implementation. Regarding institutions, 70% of the top-ranked research organizations are based in the United States. Harvard Medical School leads with 106 publications, and its affiliations with Brigham & Women's Hospital and Massachusetts General Hospital reflect close institutional partnerships. Despite some existing collaborations, cross-institutional and international cooperation remains limited, particularly between U.S. institutions and those in other countries. Strengthening global collaboration is therefore essential to promote sustained growth and advancement in digital medicine for CVD.

Analysis of journals revealed that JMIR mHealth and uHealth (IF2022 = 4.947, JCR2022 = Q1) published the highest number of studies (N = 149), followed by the Journal of Medical Internet Research (IF2022 = 7.076, JCR2022 = Q1) and Telemedicine and e-Health (IF2022 = 5.033, JCR2022 = Q1). Notably, nine of the top ten journals listed in **Table 2** are ranked in JCR Q1 or Q2, reflecting their prominent role in guiding research directions and providing key publication venues for scholars.

Regarding authorship, Noseworthy PA contributed the most papers (N = 30) and had the highest total link strength, followed by Redfern J and Friedman PA, each publishing over 25 articles. Noseworthy PA and Friedman PA primarily collaborate on studies related to machine learning (ML) and deep learning (DL) algorithms, while Redfern J focuses on digital medicine interventions, especially mobile phone text messaging and apps for remote management of chronic diseases like coronary heart disease (CHD). Overall, the research hotspots in this field center on early identification and diagnosis of CVD using ML and DL algorithms and remote management of chronic diseases through mobile health technologies.

High co-citation rates highlight foundational studies in a field [47]. The top 10 co-cited works **(Figure 5 and Table 4)** emphasize both technological innovation and clinical application. The most co-cited study, by Zachi I. Attia *et al*. [13], employed paired 12-lead ECG and echocardiography data from 44,959 patients to detect asymptomatic left ventricular dysfunction (ALVD), demonstrating AI-ECG's potential for early risk detection and disease prevention. Other highly cited references include clinical guidelines [39], scientific statements [48], reviews [49], and reports from the American Heart Association [50], highlighting the benefits of regular follow-up, remote monitoring, and behavioral interventions (e.g., smoking cessation, physical activity, healthy diet) to improve cardiovascular outcomes using AI and ML tools.

Several co-cited studies focused on arrhythmia and atrial fibrillation (AF). For instance, Marco V. Perez [40] used smartwatch pulse notifications and ECG patches to identify AF with high predictive value, while Attia *et al*. applied convolutional neural networks to detect AF and unexplained stroke. Halcox JPJ conducted a large RCT using the mobile ECG device AliveCor to detect AF earlier than conventional methods, providing timely interventions and reliable follow-up data [42]. Similarly, Awni Y. Hannun *et al*. [43] developed a deep neural network using single-lead ECG data from 53,877 individuals, achieving cardiologist-level diagnostic accuracy. Additionally, Clara K. Show *et al*. demonstrated that semi-personalized lifestyle interventions via mobile text messaging improved LDL-C levels and other cardiovascular risk factors over six months.

Among the top 10 co-cited works, five focused on digital devices or screening tools for arrhythmias, with four specifically targeting AF, indicating that AF is a relatively well-studied condition in digital medicine for CVD.

The integration of AI, cloud computing, IoT, and real-time data collection via smartphones, smartwatches, and tablets has enabled clinicians to monitor patients remotely, detect diseases early, and implement timely interventions.

However, current applications predominantly emphasize disease diagnosis, risk identification, and prevention, with fewer studies exploring therapeutic interventions. Most digital health data are primarily used to inform clinicians, whereas chronic disease management relies heavily on patient and family engagement. Future research should therefore shift toward patient-centered approaches, leveraging digital technologies to facilitate interactions between patients and clinicians, support health information exchange, promote informed decision-making, and encourage positive health behaviors.

Identification of future research hotspots and frontiers

Keyword co-occurrence analysis provides insights into the current hot spots and evolving trends within a field, while cluster analysis reveals the underlying knowledge structure, and timeline visualization illustrates the development of research focus over time [51]. Using these methods, we examined the keywords in digital medicine research related to CVD. The top six clusters—“heart failure,” “cardiovascular disease,” “risk factor,” “artificial intelligence,” “physical activity,” and “association”—reflect the core knowledge structure, emphasizing the role of digital medicine in advancing AI applications, risk factor identification, and other critical clinical challenges in CVD.

Timeline analysis shows that in 2004, research primarily focused on disease diagnosis and prevention, including terms such as “risk factors,” “coronary heart disease,” “diagnosis,” and “digital subtraction angiography,” indicating an early emphasis on monitoring, managing, and identifying disease risks. From 2005 to 2011, key topics broadened to include “hypertension,” “mortality,” “myocardial infarction,” “heart failure,” “risk,” and “intervention,” suggesting expanding applications of digital medicine in CVD, an increasing diversity of studied diseases, and growing methodological innovation. Over the past decade, with the widespread adoption of AI, ML, DL, and intelligent mobile device applications, research attention shifted to conditions such as AF, CHD, and HF, particularly in remote disease monitoring, compliance improvement, and lifestyle interventions. The focus has evolved from risk factor identification, diagnosis, and prevention toward early intervention, remote management, and application of ML, DL, and computational algorithms to deepen CVD research.

Digital therapy, either as a standalone approach or combined with conventional treatments, can enhance intervention effectiveness. Current research highlights several key hotspots:

First, mobile-based interventions, such as text messaging and apps, are valued for their convenience, immediacy, and broad accessibility, making them effective for long-term, personalized management of chronic CVD. These interventions support medication adherence, healthy behaviors, risk factor management, and overall prognosis. However, uncertainties remain regarding their long-term effects and measurable clinical outcomes, underscoring the need for further studies to evaluate the sustainability and clinical impact of digital interventions.

Second, leveraging ML in clinical management of AF represents a promising future direction. DL and ML methods, particularly convolutional neural networks (CNNs), have advanced AF screening by detecting asymptomatic paroxysmal AF using widely available 12-lead ECGs in high-risk populations, such as those with cryptogenic stroke. ML and DL techniques have also enhanced predictive models for AF and stroke by integrating structured and unstructured data from electronic health records and wearable devices, while optimizing treatment strategies including stroke prevention and antiarrhythmic drug therapy [52]. Despite these advances, challenges persist, including concerns over “black-box” algorithm adoption, data quality for model training, and the potential to exacerbate health disparities. Future work must ensure rigorous clinical validation, reproducibility across diverse healthcare settings, and appropriate regulatory oversight to maximize ML’s clinical potential while maintaining patient-centered care.

Third, early identification of disease risk factors, development of disease prediction models using neural networks, and applications of ML and unsupervised learning in CVD prognosis are expected to remain key research priorities. Future studies are likely to broaden the use of wearable devices and smartphones to monitor comorbid conditions such as diabetes, hypertension, hyperlipidemia, and mental health disorders, particularly in populations with low self-management or adherence. Additionally, digital interventions could be applied to long-term rehabilitation and monitoring of major adverse cardiovascular events (MACE) following procedures like percutaneous coronary intervention (PCI) or bypass surgery.

Strengths and limitations

This visualization-based bibliometric analysis provides a foundational reference for researchers to grasp the primary focuses and emerging trends in digital medicine for CVD. Nevertheless, certain limitations exist. First, although WoSCC is a highly comprehensive database, not all relevant documents were captured due to ongoing updates and inherent coverage restrictions. Second, only research and review articles in English were included, which may introduce selection bias and affect the reliability of the knowledge mapping. Third, bibliometric methods themselves can introduce bias, as noted in previous studies [53]. Despite these constraints, we implemented measures to minimize such limitations and better reflect the evolving research hotspots over time.

Conclusion

The advent of digital medicine has created a transformative approach for early detection, diagnosis, intervention, treatment, and remote monitoring of CVD. It emphasizes leveraging mobile-based interventions for chronic disease management, characterized by user-friendliness, rapid information transmission, and broad accessibility. Furthermore, this field continues to explore the clinical applications of machine learning for AF management, early risk factor identification, and the development of predictive models using neural networks and unsupervised learning to forecast CVD prognosis. This study offers a comprehensive overview that may guide and inform future research directions in digital medicine for cardiovascular health.

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