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Review article

Knowledge mapping of digital medicine in cardiovascular diseases from 2004 to 2022: A bibliometric analysis

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ABSTRACT

Objective: To review studies on digital medicine in cardiovascular diseases (CVD), discuss its development process, knowledge structure and research hotspots, and provide a perspective for researchers in this field.

Methods: The relevant literature in recent 20 years (January 2004 to October 2022) were retrieved from the Web of Science Core Collection (WoSCC). CiteSpace was used to demonstrate our knowledge of keywords, co-references and speculative frontiers. VOSviewer was used to chart the contributions of authors, institutions and countries and incorporates their link strength into the table.

Results: A total of 5265 English articles in set timespan were included. The number of publications increased steadily annually. The United States (US) produced the highest number of publications, followed by England. Most publications were from Harvard Medicine School, followed by Massachusetts General Hospital and Brigham Women's Hospital. The most authoritative academic journal was *JMIR mHealth and uHealth*. Noseworthy PA may have the highest influence in this intersected field with the highest number of citations and total link strength. The utilization of wearable mobile devices in the context of CVD, encompassing the identification of risk factors, diagnosis and prevention of diseases, as well as early intervention and remote management of diseases, has been widely acknowledged as a knowledge base and an area of current interest. To investigate the impact of various digital medicine interventions on chronic care and assess their clinical effectiveness, examine the potential of machine learning (ML) in delivering clinical care for atrial fibrillation (AF) and identifying early disease risk factors, as well as explore the development of disease prediction models using neural networks (NNs), ML and unsupervised learning in CVD prognosis, may emerge as future trends and areas of focus.

Conclusion: Recently, there has been a significant surge of interest in the investigation of digital medicine in CVD. This initial bibliometric study offers a comprehensive analysis of the research landscape pertaining to digital medicine in CVD, thereby furnishing related scholars with a dependable reference to facilitate further progress in this domain.

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1. Introduction

Cardiovascular disease (CVD) has become the first health risk among chronic non-infectious diseases [1]. Prevalence and mortality of CVD are on the rise, and there is an improved trend for younger people [2]. CVD not only poses a serious threat to human health but also places a huge socio-economic burden on society.

In the digital age, digital medicine has provided a new perspective in the early identification and diagnosis of CVD, intervention and treatment, remote monitoring as well as follow-up management. The digital medicine is one medical and public health practice supported by mobile devices (such as mobile phones, patient monitoring devices, personal digital assistants, and other wearable devices) [3]. Great breakthrough has been made in this field, especially during the COVID-19 epidemic [4]. Furthermore, it actively participates in the comprehensive management of CVD, including the utilization of artificial intelligence (AI) based electrocardiogram algorithm (AI-ECG) for promptly detection and diagnosis left atrial myopathy [5], AF events during sinus rhythm [6–10] and their subsequent effects [11,12] concealed long Q-T syndrome [7,13], aortic valve stenosis [14], asymptomatic left ventricular dysfunction (ALVD) [15,16], left ventricular systolic dysfunction [17–19], patients with low ejection fraction [12], Graves disease-associated AF, heart failure with reduced ejection fraction [20] and hyperkalemia [21], home blood pressure-centered innovative remote management for the control of hypertension [22–24]. The implementation of digital medicine interventions, such as mobile telephone text messaging and apps, for the remote management of patients with chronic diseases, especially coronary heart disease (CHD), has shown potential in enhancing lifestyle [17,21,25–28], controlling risk factors [26], and utilizing tele-rehabilitation [29]. These interventions have the potential to improve the quality of life and physical fitness of patients with heart failure (HF) [21,25,30–34]. However, up to now, some comprehensive reports on the research trends, related institutions and scholars, influential researches and the field hotspots of digital medicine in CVD are still lacking.

Bibliometrics, as a method for analyzing literature, enables the quantitative and qualitative assessment of publication output and status within a specific research domain [35,36]. Through this analysis, comprehensive information pertaining to authors, keywords, journals, countries, institutions, references, and other relevant aspects within the research field can be obtained [36]. The aim of this work is to systematically summarize and discuss studies on digital medicine in CVD from January 2004 to October 2022 by

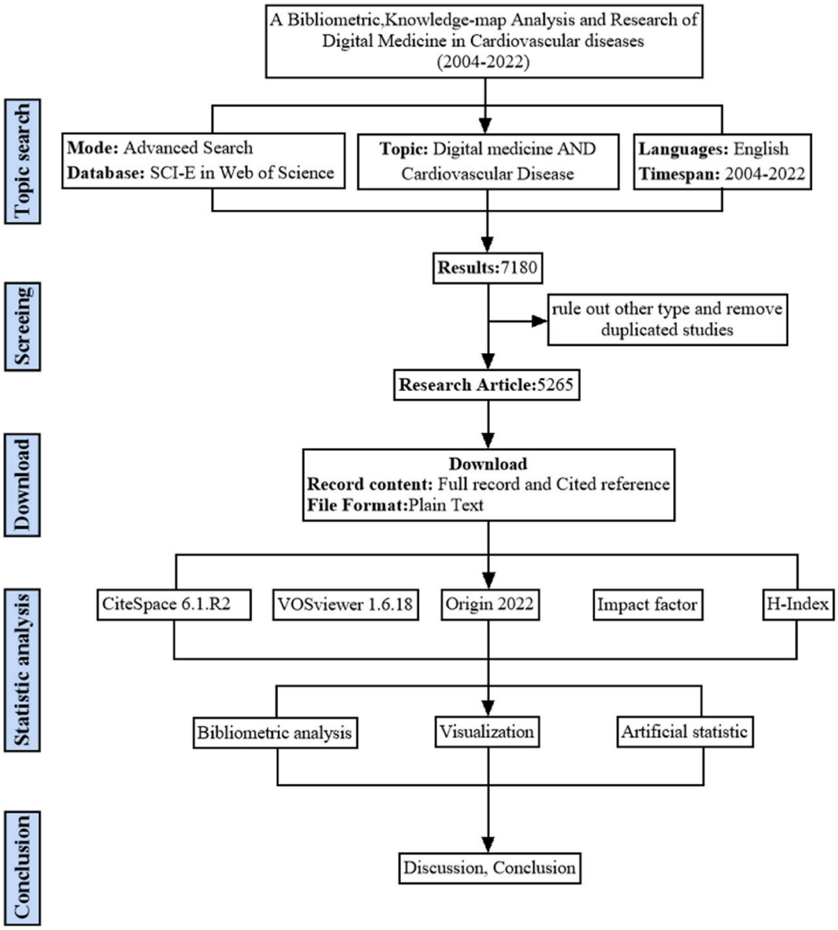

Fig. 1. Flow chart of scientific metrological analysis. SCI-E=Science citation index expand.

visualization and bibliometric analysis to indicate current hotspots and future directions for scholars in this field.

2. Materials and methods

2.1. Data acquisition

All the articles were downloaded from Web of Science Core Collection (WoSCC) on October 15, 2022. The retrieved data were collected within 1 day to avoid any potential deviation caused by daily updating. Search formula: (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))). Publication date was set as "2004-01-01" to "2022-10-15". Document types was set as "Articles". The search results were exported with "Plain Text file". Record content was chosen "Full Record and Cited References," and stored in download_*. txt format.

2.2. Data analysis and visualization

CiteSpace was used to present the knowledge of co-cited references, keywords, and speculated frontier areas. The file "download_*. txt" was imported into CiteSpace and then duplicated studies were removed. The period was set as 2004.1–2022.10 years per slice; Top N = 50 filtered the top 50 keywords and co-cited references with the highest frequency in each time slice. The network pruning was based on the preliminary analysis results to choose Pathfinder Network (PFNET), Minimum Spanning Tree (MST), or no network pruning. In the keyword co-occurrence analysis, we merged the synonyms to an alias list, including "Heart failure" and "Heart failure disease" and removed nonsense words.

Besides, VOSviewer software based on different indicators was also applied [37]. We used it to show the distribution of studies among countries, institutions and authors. Import studies were analyzed based on the full counting method, and their link strength is incorporated in tables. In addition, the up-to-date (version 2022) journal impact factor (IF) and Journal Citation Reports (JCR) of these academic journals involved were also obtained from Web of Science. H-index and Global Rank were added to the table for a comprehensive scientometric results analysis. The flow chart of scientific metrological analysis is demonstrated in Fig. 1.

3. Results

3.1. Distribution of annual publications

A total of 5265 articles about digital medicine in CVD were retrieved until October 15, 2022. The annual publication could clarify the trend and significance of an academic topic, so we present the number and growth rate of annual publications in the form of Histograms and line charts (Fig. 2). For these 20 years, the output of papers has increased steadily every year, which indicates that researchers pay more and more attention to related topics. From 2004 to 2014, the number of annual publications increased nearly four times, from 55 to 229. Then, in 2017, this number maintained a rapid growth in the following 5 years, and the number of annual publications increased from 321 to 865, an increase of nearly 22–33 %. It can be inferred that the number of publications in 2022 would be about 30 % higher than last year.

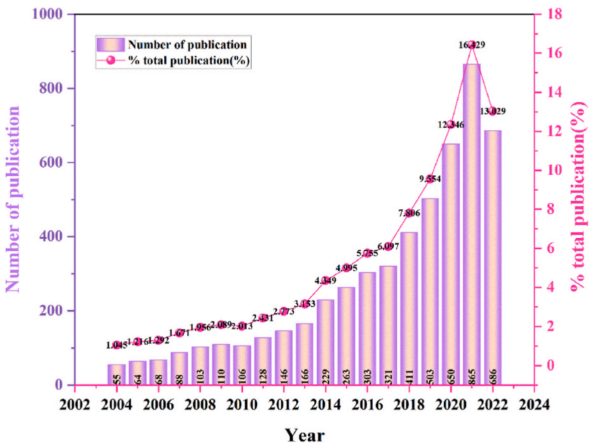

Fig. 2. The number and % total publication of annual publications relating to digital medicine in CVD from 2004 to 2022.

3.2. Distribution of countries/regions and institutions

To evaluate contributions made by different countries and institutions, and find out the potential cooperative relationships among them, we used VOSviewer to visualize the co-occurrence diagram of countries (Fig. 3A) and institutions (Fig. 3B). In addition, we listed the top 10 countries and institutions with the most publications and their total link strength in Table 1. Researchers from about 100 countries/territories contributed to the 5265 articles. The US, England, Germany, Netherlands and Italy ranked as the top five productive countries. The US published 1843 articles, which is more than the other countries, making it the most critical country in the research of digital medicine in CVD.

Among the top 10 institutions, seven belong to the US, which can explain their large proportion in the total publications. The value of total link strength indicates the cooperation between the subject and others. As shown in Table 1. The total link strength of the US is much higher than that of other countries, which is 32 % higher than that of England, which ranks second. Therefore, the US has the most cooperation with other countries in this field, and made the greatest contribution. As the three most productive institutions, Harvard Medicine School showed a slight increase in total link strength than Massachusetts General Hospital and Brigham Women's Hospital, which indicated it preferred a collaborative mode to the latter two. It is worth noting that Brigham and Women's Hospital, ranked third, is affiliated with Harvard Medical School, which further illustrates the contribution and influence of Harvard Medical School in the field. There were also certain universities, such as Sydney University, Duke University and Oxford University, whose total link strength is relatively low, but their contribution is even greater. Therefore, the value was not completely related to the contribution, but countries or institutions that are less prominent may show a strong intention to cooperate.

The H-index (high citations index) and global rank (Fig. 3C and D) are trustworthy indicators aimed at measuring an individual's scientific achievements or influence [38] and offer a reliable metric for a scientist's academic evaluation [39]. By combining countries with institutes, the US has an H-index of 2711 and is home to several world-famous institutions. Compared with other countries/regions, it has an obvious advantage, and has made outstanding contributions to digital medicine in CVD. England (1707), Germany (1498) and Netherlands (1206) also made outstanding contributions to this field.

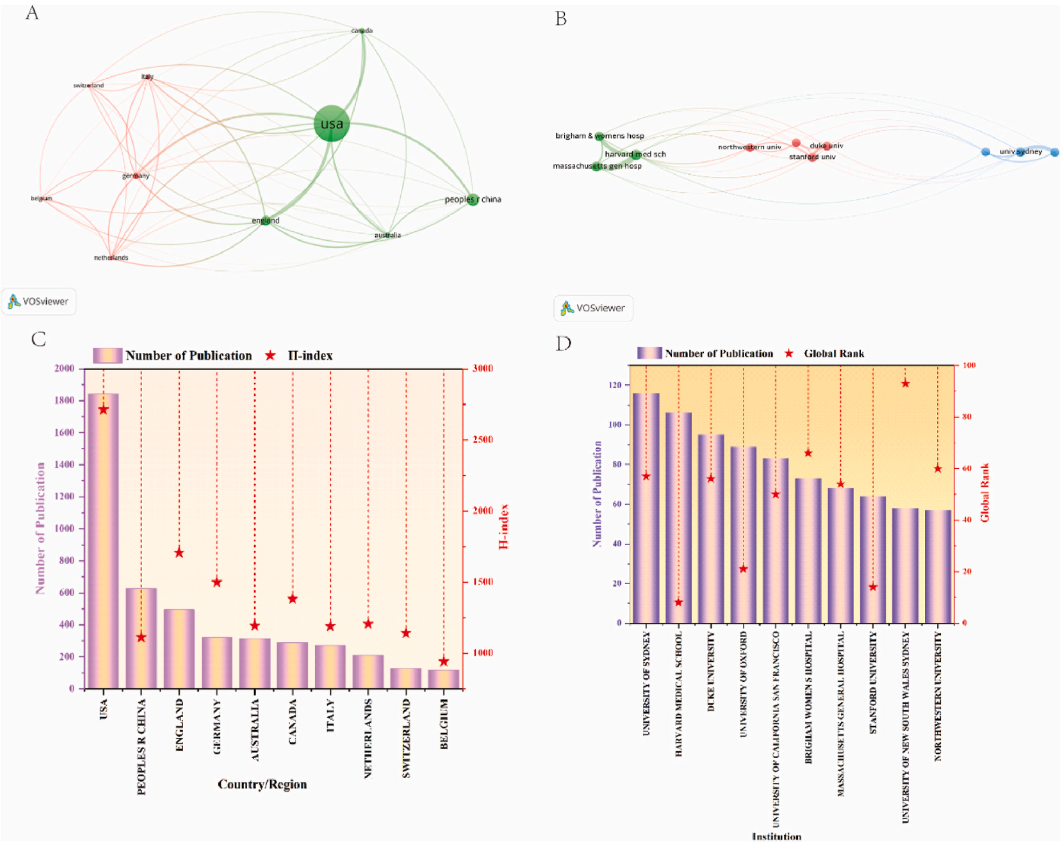

Fig. 3. The analysis of related countries/regions and institutions. (A) Network of countries/regions engaged in the research. (B) Network of institutions engaged in the research. (C) Number of publications and H-Index scores for countries/regions. (D) Number of publications of institutions and global institutional rank. In Fig. 3A and B two networks, the larger the node, the greater the contribution of the country or institution to this field. The strength of the link between two nodes indicates their cooperation. The wider the link, the closer cooperation between them.

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

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

3.3. Distribution of journals and authors

About 1481 journals were published and over 29,520 authors contributed to a total of 5265 publications. Table 2 lists the top 10 journals and four of them are from the US. *JMIR mHealth* and *uHealth* published the most abundant articles (149 papers, 2.830 %), followed by *Journal of Medical Internet Research*, which published 141 papers (2.678 %) and *Telemedicine and e-health* which published 108 papers (2.051 %). We applied VOSviewer to create the co-authorship map to find potential collaborations among different authors. Fig. 4 showed the network of authors, and Table 3 listed the top 10 high-yield authors and their total link strength. In the author network, the largest node was Noseworthy PA, who had the most relevant publications (30 articles, 0.570 %) in the field. And he had the highest total link strength (111), which representing his closest collaboration with other authors. By contrast, the total link strength of Freedman B was much lower than that of other authors, which indicated that he was more inclined to study independently.

3.4. Distribution of co-cited references and reference burst

Co-citation refers to the frequency with which two documents are cited at the same time. Table 4 displays the top 10 co-cited references, in which co-citation appears at least 26 times. "Screening for cardiac contractile dysfunction using an artificial intelligence-enabled electrocardiogram" [15], authored by Attia Z and published in *NAT MED* was the most co-cited reference in digital medicine in CVD, followed by a Guidelines entitled "2016 ESC Guidelines for the diagnosis and treatment of acute and chronic heart failure: The Task Force for the diagnosis and treatment of acute and chronic heart failure of the European Society of Cardiology (ESC) Developed with the special contribution of the Heart Failure Association (HFA) of the ESC" [40], which authored by Ponikowski P and published in *Eur Heart J*. In total, half of the top 10 most highly co-cited papers were applications of smart devices or screening tools in the field of arrhythmia, including "Screening for cardiac contractile dysfunction using an artificial intelligence–enabled electrocardiogram" [15], "Large-Scale Assessment of a Smartwatch to Identify Atrial Fibrillation" [41], "An artificial intelligence-enabled ECG algorithm for the identification of patients with atrial fibrillation during sinus rhythm: a retrospective analysis of outcome prediction" [42], "Assessment of Remote Heart Rhythm Sampling Using the Alive Cor Heart Monitor to Screen for Atrial Fibrillation" [43], "Cardiologist-Level Arrhythmia Detection and Classification in Ambulatory Electrocardiograms Using a Deep Neural Network" [44].

Cluster analysis is a statistical method to classify data according to similarity, which aims at finding the distribution of research content on a specific topic [15,45]. Modularity (Q-score) and Silhouette (S-score) are used to evaluate the cluster mapping. $Q > 0.3$ indicates that the structure of the described associations is important, $S > 0.5$ indicates that clustering is reasonable, and $S > 0.7$ indicates that clustering is efficient and persuasive., and CiteSpace was applied to cluster keywords. Fig. 5 ($Q = 0.7831$, $S = 0.9099$) displays the maximum connected components of the co-occurrence and clustering graph with untrimmed references, which contains 1002 nodes and 3390 connections (Density = 0.0068). Eleven clusters were extracted and labeled by "#" in the cluster map (Fig. 5 shows the top 9 clusters).

Table 2
Top 10 journals published most articles in the research.

Rank	Journal	Frequency (%) N = 5265	IF 2022/JCR 2022	Country affiliation
1	JMIR mHealth and uHealth	149(2.830 %)	4.947/Q1	Canada
2	Journal of Medical Internet Research	141(2.678 %)	7.076/Q1	Canada
3	Telemedicine and e-health	108(2.051 %)	5.033/Q1	United States
4	BMJ Open	107(2.032 %)	3.006/Q2	United Kingdom
5	PLoS One	81(1.538 %)	3.752/Q2	United States
6	Journal of Telemedicine and Telecare	64(1.216 %)	6.344/Q1	United Kingdom
7	BMC Public Health	55(1.045 %)	4.135/Q2	United Kingdom
8	Journal Of Chromatography B-analytical Technologies In The Biomedical And Life Science	50(0.950 %)	3.318/Q2	Netherlands
9	Trials	50(0.950 %)	2.728/Q4	United Kingdom
10	Frontiers in Cardiovascular Medicine	49(0.931 %)	5.846/Q2	Switzerland

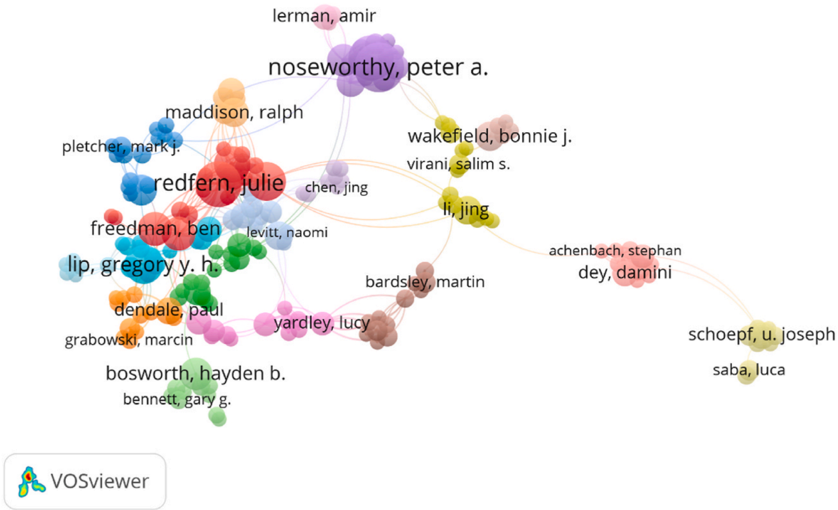

Fig. 4. The network of authors contributed to the research about digital medicine in CVD from 2004 to 2022.

Table 3
Top 10 active authors in the research.

Rank	Author	Frequency (%) N = 5265	Total link strength
1	Noseworthy PA	30(0.570 %)	67
2	redfern, julie	27(0.513 %)	42
3	friedman, paul a	26(0.494 %)	68
4	chow, dara k	21(0.399 %)	34
5	lip, gregory y. h	21(0.399 %)	0
6	thiagalingam, aravinda	19(0.361 %)	29
7	neubeck, lis	17(0.323 %)	23
8	cafazzo, joseph a.	17(0.323 %)	21
9	freedman,ben	17(0.323 %)	11
10	lopez-jimenez,francisco	16(0.304 %)	45

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

Rank	Frequency	Author	Year	Source	Co-cited reference
1	46	Attia Z	2019	Nat Med	Screening for cardiac contractile dysfunction using an artificial intelligence-enabled electrocardiogram (10.1038/s41591-018-0240-2)
2	43	Ponikowski P	2016	Eur Heart J	2016 ESC Guidelines for the diagnosis and treatment of acute and chronic heart failure: The Task Force for the diagnosis and treatment of acute and chronic heart failure of the European Society of Cardiology (ESC)Developed with the special contribution of the Heart Failure Association (HFA) of the ESC. (10.1093/eurheartj/ehw128)
3	41	Perez M	2019	New Engl J Med	Large-Scale Assessment of a Smartwatch to Identify Atrial Fibrillation. (10.1056/NEJMoa1901183)
4	41	Attia Z	2019	Lancet	An artificial intelligence-enabled ECG algorithm for the identification of patients with atrial fibrillation during sinus rhythm: a retrospective analysis of outcome prediction (10.1016/S0140-6736(19)31721-0)
5	38	Halcox J	2017	Circulation	Assessment of Remote Heart Rhythm Sampling Using the AliveCor Heart Monitor to Screen for Atrial Fibrillation: The REHEARSE-AF Study. (10.1161/CIRCULATIONAHA.117.030583)
6	37	Hannun A	2019	Nat Med	Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network. (10.1038/s41591-018-0268-3)
7	36	Burke L	2015	Circulation	Current Science on Consumer Use of Mobile Health for Cardiovascular Disease Prevention: A Scientific Statement From the American Heart Association. (10.1161/CIR.0000000000000232)
8	31	Johnson K	2018	J Am Coll Cardiol	Artificial Intelligence in Cardiology. (10.1016/j.jacc.2018.03.521)
9	30	Benjamin E	2019	Circulation	Heart Disease and Stroke Statistics-2019 Update: A Report From the American Heart Association. (10.1161/CIR.0000000000000659)
10	26	Chow C	2015	Jama-j Am Med Assoc	Effect of Lifestyle-Focused Text Messaging on Risk Factor Modification in Patients With Coronary Heart Disease: A Randomized Clinical Trial. (10.1001/jama.2015.10945)

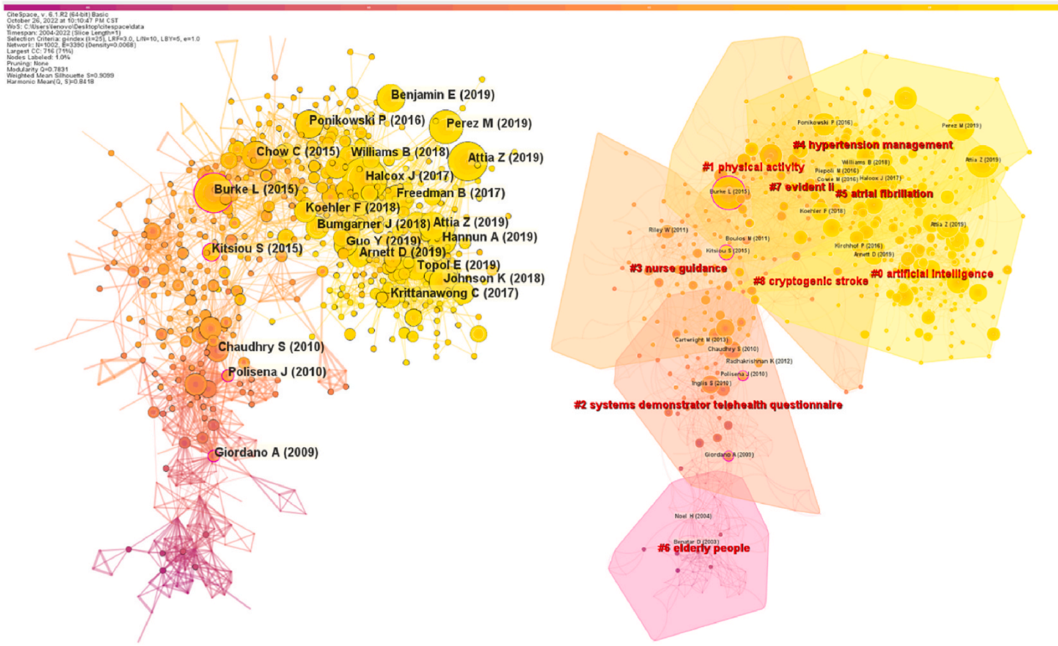

Fig. 5. The analysis of co-citation network of references from publications on the research about digital medicine in CVD from 2004 to 2022.

The largest cluster (#0) has 128 members, and the contour value is 0.907. It is labeled as artificial intelligence by LLR. The second largest cluster (#1) has 103 members and a silhouette value of 0.849. It is labeled as physical activity by LLR. The third largest cluster (#2) has 93 members and a silhouette value of 0.867. It is labeled as a systems demonstrator telehealth questionnaire by LLR. The 4th largest cluster (#3) has 86 members and a silhouette value of 0.88. It is labeled as nurse guidance by LLR. The 5th category (#4) has 84 members with a profile value of 0.797. It is labeled as hypertension management by LLR. The 6th largest cluster (#5) has 65 members, and the contour value is 0.902. It is labeled as atrial fibrillation by LLR. The 7th largest cluster (#6) has 63 members and a silhouette value of 0.972. It is labeled as elderly people by LLR. The 8th cluster (#7) has 41 members and the contour value is 0.955. It is labeled as evident ii by LLR. The 9th largest cluster (#8) has 24 members and a silhouette value of 0.973. It is labeled as a cryptogenic stroke by LLR.

As shown in Fig. 6, CiteSpace detected 20 references with the most substantial citation bursts. The earliest reference with citation bursts was from 2009, entitled "Telemonitoring or structured telephone support programs for patients with chronic HF: systematic review and meta-analysis" by Clark RA. et al. [46], published in BMJ. And "2016 ESC Guidelines for the diagnosis and treatment of

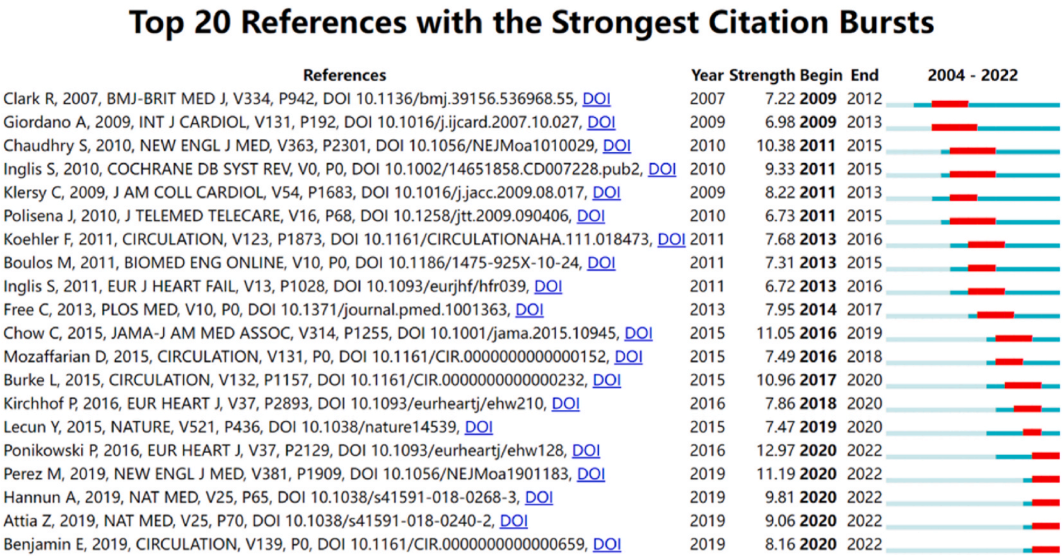

Fig. 6. Top 20 references with strongest citation bursts.

acute and chronic HF: The Task Force for the diagnosis and treatment of acute and chronic HF of the European Society of Cardiology (ESC)Developed with the special contribution of the HFA of the ESC" published by Ponikowski P et al. [40] in Eur Heart J, which had the strongest burstness (strength = 12.97).

3.5. *Distribution of keyword co-occurrence, clusters, and burst*

CiteSpace was used to build a keyword co-occurrence graph and clustered the keywords (Fig. 7). A total of 42 terms appeared more than 25 times. Table 5 shows t the co-occurrence terms of the top 20 keywords. "heart failure (515)", "artificial intelligence (399)", "hypertension (379)", "atrial fibrillation (359)", "mobile health (215)" and "physical activity (170)" are core contents of digital medicine in CVD. "cardiovascular disease", "management", "heart failure", "artificial intelligence", "hypertension", "atrial fibrillation", "intervention", "mortality", "risk factor", "mobile health", "association", and "physical activity" shared "bridge" effects in the keyword co-occurrence map.

Fig. 7 (Q = 0.7128, S = 0.919) displays the maximum connected components of a graph with no pruning keyword co-occurrence and clustering, which contains 42 nodes and 52 connections (Density = 0.0604). Six clusters were extracted and labeled by "#" in the cluster map. Cluster #0 labeled theme by "heart failure" contained 8 co-occurrence keywords: myocardial infarction, digital subtraction angiography, adherence, diagnosis, impact, outcome, care and management. The #1 "cardiovascular disease" cluster included 7 keywords: digital health, coronary heart disease, prevention, mortality, health, blood pressure and risk. The #2 cluster was related to "risk factor", which included 8 keywords: performance liquid chromatography, population, human plasma, validation, prevalence, risk factor, hypertension, and disease. Cluster #3 focused on the "artificial intelligence" topic and had 7 keywords in the cluster, including stroke, classification, coronary artery disease, deep learning, machine learning, mobile health and atrial fibrillation. The #4 "physical activity" cluster contained 5 keywords, including quality of life, mobile phone, randomized controlled trial, meta-analysis and intervention. The #5 "association" cluster contained 2 keywords, including guideline and adult. The keywords timeline view displayed the evolution of high-frequency keywords. Fig. 8 shows the development path of research hotspots of digital medicine in CVD. From 2004 to 2011, research keywords in this area focused on acute myocardial infarction, chronic HF, hypertension, atrial fibrillation, digital subtraction angiography, performance, quantification and quality of life. From 2012 to 2022, the primary terms were technology, telemedicine, telehealth, big data, primary care, wearable device, mobile application, smartphone app, echocardiography, chronic disease and mental health. Keywords burst detection identifies sudden increases of frequency in a short time, reveals the research hotspots in a period, and reflects the evolution trend of hotspots. The top 20 keywords with citation bursts were shown in Table 6 and Fig. 9. The time span is set to 2004 to 2022 and is shown as the green line, while the time period of keyword explosion is indicated by the red line. After 2017, the strongest keywords cited for outbreaks in the last five years were "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).

4. Discussion

4.1. *Knowledge base of digital medicine in CVD*

The initial emergence of Baldassarre, D. et al.'s scholarly perspectives involved an assessment of the potential of ANN to identify individuals with or without a prior history of vascular events. This evaluation was based on the analysis of vascular risk factors, carotid ultrasound variables, or a combination of both. The findings of their study revealed that ANN holds significant promise in the advancement of precise diagnostic instruments aimed at identifying patients at elevated risk of CVD [47]. Over the past two decades, there has been a consistent increase in the number of documents, with a particularly notable growth rate observed in the last five years.

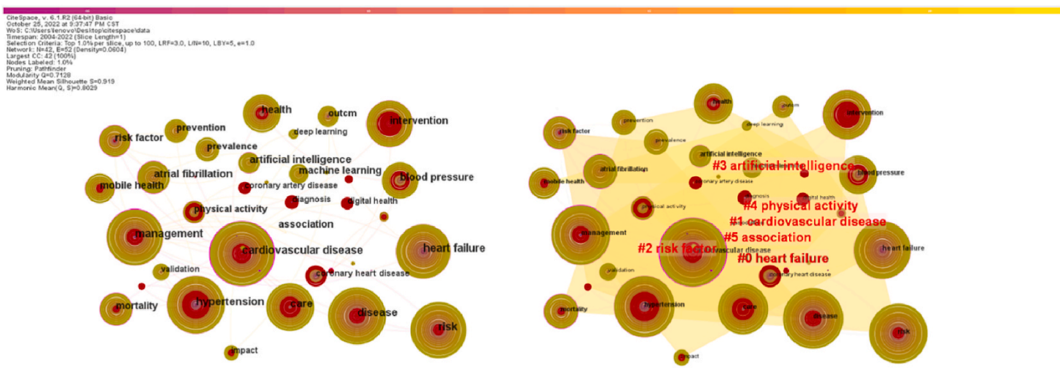

Fig. 7. The analysis of keywords relating to the research about digital medicine in CVD from 2004 to 2022. The larger the cross is, the higher frequency each keyword has.

Table 5
Top 20 keywords in terms of frequency 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

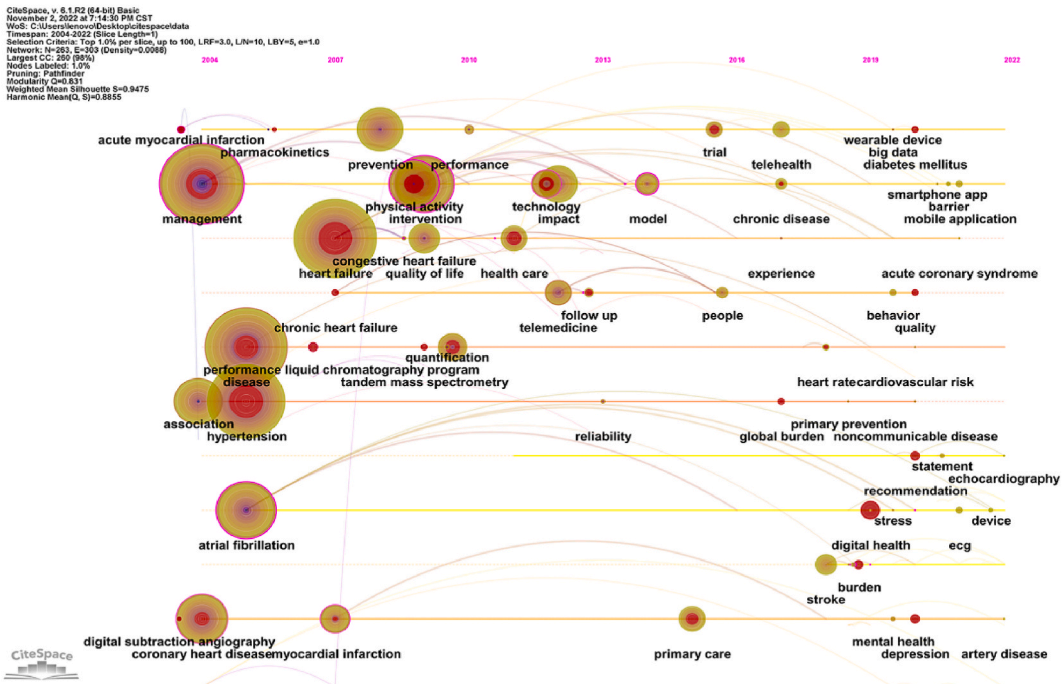

Fig. 8. Keywords timeline view of digital medicine in CVD from 2004 to 2022.

Notably, significant advancements have been achieved in the field of digital medicine, highlighting its crucial role in addressing CVD. This observation underscores the sustained interest and ongoing relevance of this field as a prominent research topic. In this research, a comprehensive collection of 5265 articles pertaining to digital medicine in CVD was identified in the Web of Science Core Collection (WoSCC) database, spanning from January 2004 to October 2022. Notably, the publications released within the initial ten months of 2022 constituted nearly 30 % of the cumulative output over the preceding five-year period, as depicted in Fig. 2. This observation highlights the escalating significance and widespread appeal of this particular domain.

In the analysis of countries/regions and institutions, it is worth noting that 90 % of the top 10 countries listed in Table 1 are classified as developed countries, with China being the sole developing country. This observation suggests that, among the countries focusing on this topic, developed nations like the United States and the United Kingdom take the lead, while developing countries such as China exhibit comparatively less attention towards this issue. It was observed that the initiation of research and development for digital medicine products in China occurred comparatively later. In November 2020, the National Medical Products Administration

Table 6
Top 20 keywords with the strongest citation bursts and last until 2022.

Keyword	Strength	Begin
risk factor	6.57	2004
disease	19.87	2006
human plasma	14.3	2006
risk	11.03	2007
cardiovascular disease	13.09	2008
management	10.23	2010
hypertension	36.43	2011
intervention	19.45	2011
care	14.08	2012
mortality	7.61	2013
randomized controlled trial	18.78	2014
health	6.65	2014
Meta analysis	19.69	2015
mobile health	9.06	2015
guideline	21.88	2018
impact	7.96	2018
classification	19.45	2020
digital health	15.85	2020
coronary artery disease	15.18	2020
diagnosis	11.82	2020

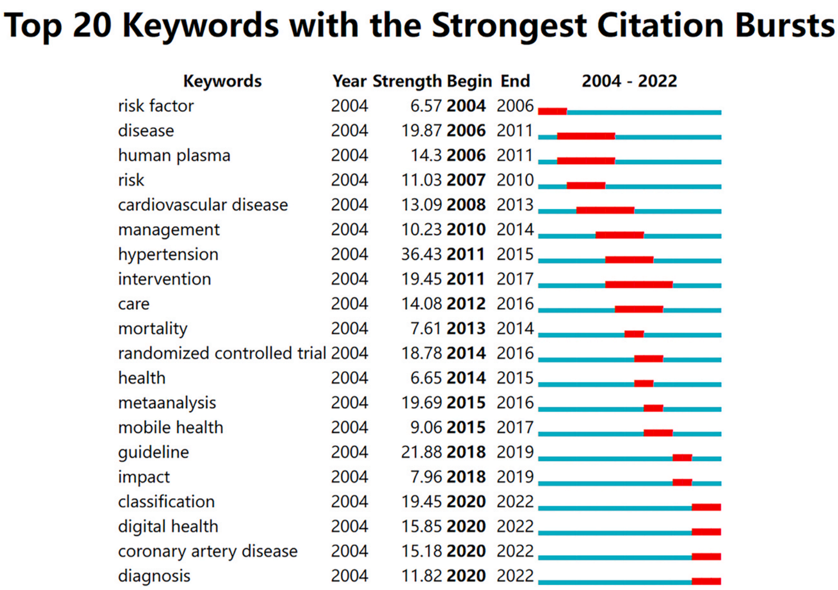

Fig. 9. Top 20 keywords with citation burst (sorted by the beginning year of the burst).

(NMPA) granted approval for the inaugural digital therapy product. Nevertheless, the substantial prevalence of patients afflicted with chronic CVD such as CHD, hypertension (HT), and HF in China indicates significant prospects for digital medicine interventions centered around lifestyle modifications within the Chinese market. Furthermore, the robust advancement of China's mobile internet infrastructure serves as a firm technological basis for the progress of digital medicine in the country. Hence, it is imperative to enhance collaboration and communication among nations and institutions to foster the robust advancement of digital therapy in China. Regarding notable establishments, within the top decile of research institutions, 70 % are situated in the United States, with Harvard Medicine School exhibiting the highest number of publications (N = 106). Furthermore, its affiliation with Brigham & Women's Hospital and Massachusetts General Hospital demonstrates a close partnership. It is noteworthy that all three aforementioned institutions are located within the United States, with Brigham & Women's Hospital being directly affiliated with Harvard Medicine School. However, despite the existence of cooperative relations among certain nations, the extent and intensity of collaboration between institutions remain suboptimal. Notably, the level of cooperation between institutions in the United States and other countries is limited. Evidently, this circumstance is poised to impede the long-term advancement of the research domain. Hence, it is highly recommended that research institutions across different nations engage in comprehensive collaboration and communication to collectively advance the progress of digital medicine in CVD.

In the analysis of academic journals, it was found that *JMIR mHealth and uHealth* (F_{2022} = 4.947, JCR_{2022} = Q1) published the highest number of studies (N = 149), followed by the *Journal of Medical Internet Research* (IF_{2022} = 7.076, JCR_{2022} = Q1) and *Telemedicine and e-health* (F_{2022} = 5.033, JCR_{2022} = Q1). It is worth noting that the majority of the journals (9 out of 10) listed in Table 2 are ranked in the JCR Q1 and Q2 regions, indicating their significant role in this field and providing guidance for scholars in terms of submission and publication opportunities.

In the examination of co-authors, it is observed that Noseworthy PA has contributed the highest number of relevant papers (N = 30) and holds the top position in terms of total link strength, followed by Redfern J and Friedman PA. They have demonstrated a remarkable productivity with a publication rate exceeding 25 articles per capita. It is worth mentioning that Noseworthy PA and Friedman PA have established a strong collaborative bond, primarily concentrating on research pertaining to ML and deep learning (DL) algorithms. Meanwhile, Redfern J mainly focused on researches digital medicine intervention. In particular, mobile telephone text messaging and apps, remote management of patients with chronic diseases (especially CHD). In general, the above research mainly focuses on the early identification and diagnosis of some CVD by ML and DL algorithms, as well as the remote management of patients with chronic diseases such as CHD by mobile health interventions such as mobile telephone text messaging and apps, which are the hot spots and focuses of researchers in this field.

Research with a high co-citation rate is often considered the research foundation of a certain field [48]. Through bibliometric analysis, we identified the top 10 studies in this field with a total citation rate (Fig. 5, Table 4). The specific description and summary are as follows:

The first co-cited research was a convolutional neural network conducted by Zachi I. Attia and his colleges [15]. They use paired 12-lead electrocardiogram (ECG) and echocardiography data from 44,959 patients at the Mayo Clinic to identify patients with ALVD. The result confirmed that the ability of AI-ECG in diagnosing ALVD in asymptomatic individuals, with important clinical significance for early detection of individuals at risk of ventricular dysfunction and prevention of disease progression. It also provided a direction for the application of digital medicine in the field of ECG.

The second, seventh, eighth, and ninth co-cited article are guideline [40], scientific statement [49], review [50], and the report from American Heart Association [51], respectively. They described the benefits of regular follow-up and remote biomedical monitoring for patients with HF. Retrospective analysis of real-time data collected by mobile devices on healthy behaviors (such as smoking, physical activity, healthy eating, and maintaining a healthy weight) and CV health indicators (such as blood glucose, blood lipids, blood pressure, and BMI) related to beneficial CV risk factors, in order to guide CV medicine in terms of behavioral intervention measures. Explain how to apply AI and ML tools to achieve accurate cardiology and improve patient outcomes. Report the latest data on CV health monitoring and benefits in the population, and evaluate and monitor indicators of healthy eating. The influential and credible studies above reflect the rapid development of digital medicine in the field of CVD, and to some extent, its importance in previous studies.

The third co-cited research done by Marco V. Perez [41] identified possible AF based on an irregular pulse notification algorithm of a smart watch application, and then delivered ECG patch to monitor the occurrence of subsequent AF. Among participants enrolled, they were notified irregular pulses with positive predictive values 0.84 (95 % CI, 0.76 to 0.92) and 0.71 (97.5 % CI, 0.69 to 0.74), respectively. The fourth co-cited research was also designed to apply ECG based on convolutional neural networks by Zachi I Attia to detect image characteristics of patients with occasional AF, thereby providing personalized identification of AF screening and unexplained stroke. In addition, the fifth co-cited research was a large sample randomized controlled trial (RCT) on mobile medical device to screen AF published by Halcox JPJ. The purpose was to evaluate whether AliveCor (an iPod based ECG monitoring device supported by wireless networks) combined with mobile devices could diagnose AF earlier than traditional screening methods so that to provide early intervention and reduce the occurrence of serious complications. It was suggested that the new long-term cardiac monitoring device could effectively and long-term capture and upload user ECG data, timely diagnose, screen and intervene in the occurrence of AF, and also provide clinicians with effective and reliable follow-up monitoring data [43]. The sixth co-cited research was a deep neural network developed by Awni Y. Hannun et al. [44] based on 53877 individuals using single lead ambulatory ECG monitoring data, which had high diagnostic performance similar to that of cardiologists. The widely available digital ECG data and DL algorithm paradigm provided opportunities to significantly improve the accuracy and scalability of automated ECG analysis. In addition, the tenth co-cited research was a study by Clara K. Show et al., which used mobile phone text messaging to provide lifestyle focused semi personalized support interventions for patients with CHD for 6 months. The results showed that this method can significantly improve LDL-C levels in patients with CHD, while also significantly improving other CVD risk factors such as blood pressure, BMI, and smoking status, which had been widely recognized.

Among the top 10 most commonly cited articles, five were applications of intelligent devices or screening tools based on digital medicine in the field of arrhythmia, and four of the five studies were applications in AF screening. This indicated that AF was a relatively mature disease in the field of CVD research in digital medicine. In recent years, the development of new technologies such as AI, cloud computing, and the Internet of Things has provided a technological foundation for digital medicine. Mobile devices that allow real-time data collection, such as smartphone software, smart watches, and tablets, are becoming increasingly popular, enabling doctors to remotely access patient information, monitor and evaluate patient real-time conditions through information, detect diseases early, and develop appropriate intervention measures. However, based on the analysis of the above studies, we found that the current application of digital medicine in CVD field was mainly in the diagnosis, identification, and prevention of diseases, while there were few studies on intervention as a therapeutic means. The results collected through digital technology or methods were mostly fed back to clinicians. However, in the management process of chronic diseases, due to the limitations of patients' age, economic issues, time and space, and other factors, patients and their families were the "main battlefield" of disease management. Therefore, we believed that the following research shall consider the overall situation of the disease and paid more attention to the management of patients and their families, involve individuals in preventing or managing diseases, so the research direction of digital medicine shall focus more on interacting with patients. Support the exchange of health information between patients and between patients and doctors through digital technology mediated tools, promote health decision-making, and encourage positive health behaviors.

4.2. Identification of research hotspots and frontiers in the future

Keyword co-occurrence analysis reflects the hot spots and research trends of a certain academic topic. Keyword cluster analysis shows the knowledge structure, and timeline view visualizes the keyword hotspot evolution [52]. Based on the above three methods, we analyzed the keywords of digital medicine related research in the field of CVD. From the visualization of top 6 keywords-cluster analysis, "heart failure", "cardiovascular disease", "risk factor", "artificial intelligence", "physical activity", and "association" constructed the knowledge structure. It reflected the crucial role of digital medicine in the development of AI for CVD, risk factor identification, and other key clinical issues. From the perspective of timeline analysis, the keywords used in 2004 were closely related to the diagnosis and prevention of diseases, including "risk factors", "coronary heart disease", "diagnosis", and "digital subtraction angiography", indicating that the initial research focus was on disease diagnosis, risk factor identification, and disease monitoring and management. From 2005 to 2011, the key themes gradually enriched, including "hypertension", "mortality", "myocardial infarction", "heart failure", "risk", "intervention", etc., indicating that the application of digital medicine in CVD continues to expand, the disease spectrum of research continues to increase, and research methods and topics continue to innovate and deepen. In the past 10 years, with the continuous exploration of digital medicine in the field of CVD by scholars, such as AI, ML, DL, and other methods intelligent mobile device applications, diseases such as AF, CHD, and HF related to remote disease monitoring and compliance improvement turned to new hot spots. Research had expanded from initial identification of risk factors, diagnosis, and prevention of diseases to early intervention and remote management of diseases, as well as lifestyle interventions using remote mobile devices to improve quality of life and compliance. It also relied on digital technology to apply ML, DL, and computer algorithms to conduct in-depth research in the field of CVD.

Digital therapy could be used as a single therapy or in combination with other currently available therapies to enhance the intervention effectiveness of other therapies. Based on the above research results, we found that the research hotspots of digital therapy in the field of CVD mainly was focused on:

Firstly, the study above revealed that the ease of use, immediate transmission of information, and limitless accessibility render telephone text messages or apps an appealing tool for the long-term personalized remote management of chronic CVD, which is beneficial for medication compliance, healthy behavior and lifestyle, risk factors control, as well as prognosis of CVD. However, there is still a lack of certainty regarding the magnitude of the impact of digital medicine interventions over extended durations and on quantifiable indicators of outcomes. Further investigation is required to determine the advantages of various aspects of digital medicine interventions, the sustainability of their effects, and their influence on objective clinical measures of outcomes. This research will aid in gaining a clearer understanding of the role of digital medicine interventions in the management of chronic diseases.

Secondly, investigating the potential of ML in delivering clinical care for AF could be a promising avenue for future research. In recent years, the utilization of DL and ML techniques, specifically convolutional neural networks (CNNs), has facilitated the advancement of AF screening pathways. These pathways employ the widely available 12-lead electrocardiogram (ECG) to identify asymptomatic paroxysmal AF in high-risk populations, such as individuals with cryptogenic stroke. Additionally, DL and ML methods have contributed to the enhancement of AF and stroke prediction models by employing comprehensive digital phenotyping techniques. These techniques involve the extraction of structured and unstructured data from electronic health records and wearable monitoring technologies. Furthermore, DL and ML have played a crucial role in optimizing treatment strategies, encompassing stroke prevention and the monitoring of antiarrhythmic drug (AAD) therapy [53]. As the clinical and population-wide implications of these tools are further explored, it becomes evident that significant advancements are accompanied by certain obstacles. These challenges encompass apprehensions regarding the adoption of opaque technologies, the evaluation of input data quality for model training, and the potential for exacerbating health disparities rather than mitigating them. Consequently, what measures need to be undertaken to fully harness the capabilities of machine learning? The rigorous research platform should encompass clinical validation, internal and external replication consistency, and generalizability across diverse healthcare settings, irrespective of resource availability. Additionally, regulatory considerations must be taken into account to effectively harness the potential of ML while maintaining a patient-centered approach in the management of AF.

Furthermore, early identification of disease risk factors, disease prediction models based on NNs, and applications of ML and unsupervised learning in CVD prognosis will also become research hotspots. We speculate that in the future, while broadening and deepening the above research hotspots, we will continue to expand the application scope of wearable devices and smart phones in CVD field, such as comorbidity diabetes, HT, hyperlipidemia, mental health diseases and other diseases with high drug compliance or low self-management level. And regular rehabilitation management and major adverse cardiovascular events (MACE) monitoring after CV surgery such as percutaneous coronary intervention (PCI) or bypass surgery.

4.3. Strengths and limitations

The visualization-based literature analysis laid a basis foundation for researchers to understand the focus and potential trends of digital medicine in CVD. However, there were still some limitations. Firstly, data were collected from WoSCC, which is one of the most comprehensive databases, yet not all documents were completely obtained for keep updating and limitation of coverage. Secondly, publication types included were only research and review, and all were written in English. Selection bias might damage the reliability of knowledge map. Thirdly, the applications of bibliometrics might lead to bias, as reported in other bibliometrics studies [54].

However, we tried to work around these deficiencies to more accurately reflect the of research hotspots in different periods.

5. Conclusion

The emergence of digital medicine has led to the establishment of a new paradigm in the early identification and diagnosis, intervention and treatment, as well as remote monitoring and follow-up management of CVD. It aims to explore the utilization of mobile intervention methods, such as ease of use, instantaneous relay of information, and wide accessibility, for managing chronic diseases. Additionally, it seeks to further investigate the potential of ML in delivering clinical care for AF and early identification of disease risk factors. The analysis also explores the development of disease prediction models based on NNs and the applications of ML and unsupervised learning in predicting the prognosis of CVD. It is believed that this study has the potential to provide valuable insights for researchers in future research endeavors.

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CRediT authorship contribution statement

Ying Chen: Writing – review & editing, Writing – original draft, Conceptualization. **Xiang Xiao:** Writing – original draft, Conceptualization. **Qing He:** Writing – original draft, Data curation. **Rui-Qi Yao:** Writing – original draft. **Gao-Yu Zhang:** Writing – original draft. **Jia-Rong Fan:** Writing – original draft. **Chong-Xiang Xue:** Supervision, Project administration. **Li Huang:** Supervision, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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