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Discovering and Visualizing Knowledge Evolution of Chronic Disease Research Driven by Emerging Technologies

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ABSTRACT The aging population and an unhealthy lifestyle have led to a considerable proportion of chronic diseases in many countries. A new generation of emerging technologies has set off a new wave of revolution around the world, such as cloud computing, the Internet of Things, artificial intelligence, and so on. In recent years, the literature associated with chronic disease research driven by emerging technologies has grown rapidly, but a few studies have used bibliometrics and a visualization approach to conduct deep mining and reveal a panorama of this field. This paper is a bibliometric analysis of chronic disease research driven by emerging technologies, and this paper analyzed and visualized the time distribution, space distribution, literature co-citation, and research focus. Moreover, this paper visualized and determined the dynamic knowledge structure of chronic disease research driven by emerging technologies, which will be helpful in understanding the current research status and identifying the future research directions in this research field for e-health and medical informatics scholars.

INDEX TERMS Emerging technologies, chronic diseases, bibliometrics, data visualization, healthcare informatics.

I. INTRODUCTION

Chronic diseases, also known as chronic non-communicable diseases, is a disease that has a long course, a complex cause, and can hardly be completely cured [1], common chronic diseases include hypertension, cirrhosis, rheumatoid arthritis, diabetes, cerebral hemorrhage. The aging population and an unhealthy lifestyle have led to a considerable proportion of chronic diseases, such as diabetes and heart diseases, in many countries [2]. The impact of chronic diseases on the human body is long-lasting and far-reaching, and it is one of the leading causes of human death [3]. About 60% of deaths worldwide are attributed to these diseases, and approximately 80% of deaths from chronic diseases occur in low and middle-income countries [4]. In the United States, approximately 25% of adults have at least two chronic diseases [5]. An increasing number of patients with chronic diseases lead to an increase in national health care demand and cost. Providing specialized medical care to patients with chronic diseases is labor-intensive and expensive, and the outcome is frequently poor, particularly in low-income countries, which have scarce resources and lack high-quality medical care [6]. For example, Africa faces a double burden of infectious and chronic diseases, although the number of deaths caused by infectious diseases on the African continent still accounts for 69% of the total death toll, the specific mortality rate of age-related chronic diseases in sub-Saharan Africa is basically higher than in all other regions of the world [7]. Chronic diseases exert a significant economic impact on governments, families and health systems, moreover, the relationship between the formulation of national policies and international economic and political pressures has a large

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impact on the risks of chronic diseases and the ability of countries to cope with chronic diseases [8]. In general, research on chronic diseases has attracted widespread attention from scholars and governments all over the world, and the methods used in the research are also rich and varied, among them, emerging technologies are one of the methods used to study chronic diseases.

At present, a new generation of information technology is setting off a new wave of industrial revolutions around the world. The emerging technologies referred to in this study refer to some advanced methods or tools used in the research of chronic diseases, and they are widely used in various fields. For example: big data, cloud computing, Internet of Things (IoT), artificial intelligence, etc. Therefore, research literature on the field of chronic disease research driven by emerging technologies is endless. Kong *et al.* [9] used unsupervised machine learning to analyze gene expression profiles and found relevant pathways for important genes and microarray gene expression data for Alzheimer's disease. Pasluosta *et al.* [10] proposed to connect the wearable sensor to the medical database so that the sports indicators of Parkinson's disease can be obtained instantly. Kelarev *et al.* [11] applied decision tree integration to the detection and monitoring of cardiac autonomic neuropathy (CAN) in diabetic patients. Jara *et al.* [12] developed a personal device based on the Internet of Things to assist in calculating the dose of insulin. Yu *et al.* [13] proposed a support vector machine (SVM) model for classifying people with and without a common chronic disease. Austin *et al.* [14] pointed out that tree mining based on data mining and machine learning has better performance in predicting and classifying the probability of heart failure (HF) than traditional classification and regression tree methods. Matarić *et al.* [15] developed a socially assisted robot focused on non-contact patient/user assistance to help patients recover from stroke. Yeh *et al.* [16] applied a classification technique and method to construct a predictive model of cerebrovascular disease. Guessoum *et al.* [17] proposed a decision support system for chronic obstructive pulmonary disease based on the principles of case-based reasoning. Kaczmarczyk *et al.* [18] explored three homogeneity classification methods for gait patterns in patients after stroke, with artificial neural networks performing best. Stroke, Alzheimer's disease and diabetes are relatively common chronic diseases and have received wide attention from scholars. Stroke is a chronic disease that causes cell death due to insufficient blood flow to the brain, and there are two main types of stroke: ischemic stroke (due to lack of blood flow) and hemorrhagic stroke (due to bleeding) [19]. The main risk factors for stroke include high blood pressure, obesity, high blood cholesterol, and diabetes [20]. Alzheimer's disease is a chronic neurodegenerative disease that is the cause of 60-70% of dementia cases, the most common early symptom is that it is difficult to remember what has happened recently [21]. As the disease progresses, symptoms may include language barriers, disorientation (including easy getting lost), mood swings, loss of motivation, lack of self-care, and behavioral problems. Diabetes is a disease caused by the inability of the pancreas to produce enough insulin or the body's cells to respond appropriately to the insulin produced [22]. If left untreated, diabetes can cause many complications. Acute complications include diabetic ketoacidosis, hyperosmolar hyperglycemia or death [23]. Serious long-term complications include cardiovascular disease, stroke, chronic kidney disease and eye damage [24]. There are many causes of chronic diseases, but unhealthy lifestyles are the common culprit of most chronic diseases, including obesity, overcapacity, nutritional imbalance, sedentary, lack of exercise, and mental stress [25], [26]. There are also crossovers between different chronic diseases. For example, high blood pressure, obesity and diabetes may cause stroke, Alzheimer's disease can cause dementia, and high blood pressure can lead to complications such as cardiovascular disease and stroke. Therefore, most patients with chronic diseases suffer from two or more chronic diseases.

Due to the particularity, complexity and extensiveness of chronic diseases, coupled with the current popularity of emerging technologies research, it has spawned the field of chronic disease research driven by emerging technologies. Using emerging technologies to study chronic diseases is a general trend, and it allows for deeper analysis, more accurate predictions, and better performance than traditional tools. So many outstanding achievements and major breakthroughs has been reported in chronic disease research driven by health big data and emerging technologies. However, there are still some issues that need to be addressed and resolved: 1) there is no relevant research based on scientific evidence rather than subjective beliefs to review the current status and future development direction of chronic disease research driven by emerging technologies; 2) there is no relevant research to visualize the knowledge of the field from the perspective of bibliometrics; 3) There is no relevant research combined with the Web of Science database to conduct a review of the research results since the 21st century in this field worldwide. To fill in this research gap, based on the database of Web of Science, this study visualized the current development status, research hotspots and future development trends of the field of chronic diseases driven by emerging technologies. This paper analyzed and visualized the time distribution, space distribution, literature co-citation and research focus. Moreover, this study determined the dynamic knowledge structure of chronic disease research driven by emerging technologies, which will be helpful in understanding current research status and identifying future research directions in this research field for e-health and medical informatics scholars.

II. METHODOLOGY

A. DATA SOURCE

The literature data of this paper is derived from SCI-E, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI, CCR-E, and IC databases in the core collection of Web of Science (WOS), and advanced retrieval is selected. WOS is the world's largest comprehensive academic information resource with the largest coverage of disciplines, through which the research information of a certain discipline or a certain field can be comprehensively understood. Moreover, because WOS has strict requirements for the selected journals, the retrieved literatures have high academic value and certain representativeness [27]. The search strategy we used is as follows: TS = ((''artificial intelligence'' OR ''Internet of Things'' OR ''cloud computing'' OR ''deep learning'' OR #) AND (''diabet∗'' OR ''stroke∗'' OR ''Alzheimer's disease'' OR ''obesit∗'' OR ##)). Among them, ''∗'' indicates a wildcard, such as ''diabet∗,'' including ''diabet,'' ''diabete,'' ''diabetes'', and so on. The symbol ''#'' represents 20 other words associated with emerging technologies, and the symbol ''##'' represents 28 other words related to chronic diseases. Then, the article type was set as the article, and the publication year was set as 2000–2017. Finally, 4,820 retrieval records were obtained. The flowchart for selected publication is shown in Fig. 1.

B. TOOLKITS

In our research, we used some software tools such as HistCite, CiteSpace, and MS Excel. HistCite is a software package for bibliometric analysis and information visualization [28]. Because HistCite's statistical function is very powerful, this study mainly uses it to statistically correlate data and use MS Excel to draw charts for visualization [29]. CiteSpace mainly calculates and analyzes the literature of specific fields based on the theory of co-citation analysis and path-finding network algorithm to explore the key path and knowledge turning point and key point of the evolution of the subject field, and by drawing a series of visual maps to analyze and explore the potential dynamic mechanism of discipline evolution and the frontier of discipline development [30], [31]. In this study, CiteSpace is mainly used to analyze and visualize the author distribution, institutional distribution, national distribution, literature co-citation and research focus analysis in the field of chronic disease research driven by emerging technologies.

III. KNOWLEDGE MAP OF TIME-SPACE ANALYSIS

A. PTIME DISTRIBUTION MAP

To understand the output of research results in the field of chronic disease research driven by emerging technologies, we conducted a statistical analysis of the scientific literature over the 18 years from 2000 to 2017, and obtained the change trend of annual contents, as shown in Fig. 2. This research field began in the 1980s and 1990s. After the 21st century, emerging technologies, such as artificial intelligence, cloud computing, and Internet of Things, have rapidly developed. In addition, the understanding of chronic diseases has become deeper, with an increasing degree of emphasis, thereby allowing research in this area to flourish. From Fig. 2, the overall curve exhibits an increasing trend from 2000 to 2017. The curve from 2000 to 2014 is close to or even coincident

FIGURE 1. Flowchart for selected publications.

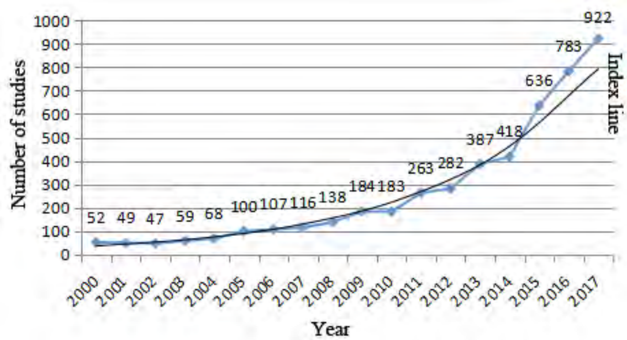

FIGURE 2. Annual number of published articles from 2000-2017.

with the Index line, so the curve is roughly in line with the exponential growth trend. By contrast, the curve growth of 2014-2017 is extremely fast, and the curve is significantly higher than the Index line and roughly assumes a linear upward trend. The research on chronic disease research

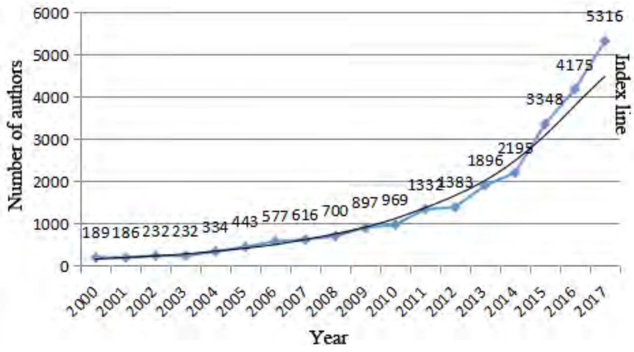

FIGURE 3. Annual number of authors from 2000-2017.

driven by emerging technologies has not reached the mature stage and is still in the growing phase, which will continue in the future.

Next, we studied the input of scientific researchers in the field of chronic disease research driven by emerging technologies. We conducted a statistical analysis on the number of scientific researchers over the years from 2000 to 2017, and obtained the change trend of annual author input, as shown in Fig. 3. Comparing Fig. 2 and Fig. 3, we can clearly find that the variation trend of the annual number of authors' curve is roughly the same as that of the annual number of published articles. This is also easy to understand: the more the annual amount of documentation, the more researchers in this field will surely be invested, and there is a positive correlation between them. As the authors' input in this field increases, the output of research achievements in this field will also increase. On the contrary, the more research results produced in a field, indicating that the research in this field is a hotspot, the more it is bound to attract more researchers to join this field.

Finally, we studied the input-output ratio of researchers in the field of chronic disease research driven by emerging technologies. We conducted a statistical analysis of the number of participants in a single article in the 18 years from 2000 to 2017, and obtained the ratio of participants to a single article. In 2000, the input-output ratio was only 3.63, and this figure continued to grow, reaching a maximum of 5.77 in 2017. From 2000 to 2017, the average number of participants in a single paper reached 4.89. The number of authors that collaborate in this research area is relatively high, which guarantees the quality of papers to a certain extent and reflects the degree of attention that researchers attach to this field.

B. SPACE DISTRIBUTION MAP

1) AUTHOR DISTRIBUTION

First, we used CiteSpace to generate an author collaboration network, as shown in Fig. 4. Table 1 lists the top 20 authors and their number of published articles. The author with the largest number of publications is Acharya, who published 44 articles, and he has an article on the WOS that has been cited more than 100. In that study, Acharya et al. proposed

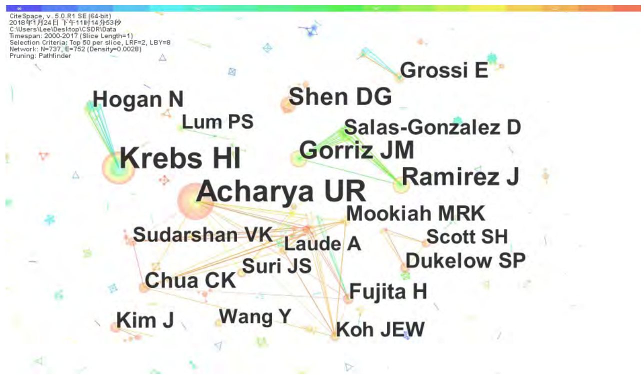

FIGURE 4. Author collaboration network in the field of chronic disease research driven by emerging technologies.

TABLE 1. List of the Top 20 authors and their number of published articles.

Author	Number of published articles	Author	Number of published articles
Acharya UR	44	Salas–Gonzalez D	12
Krebs HI	40	Dukelow SP	12
Ramirez J	21	Mookiah MRK	12
Gorriz JM	21	Koh JEW	11
Shen DG	19	Suri JS	11
Hogan N	15	Sudarshan VK	11
Grossi E	13	Scott SH	10
Chua CK	13	Laude A	10
Fujita H	13	Wang Y	10
Kim J	13	Lum PS	10

a computer-based method to detect diabetic retinopathy stages and use artificial neural networks to classify fundus images [32]. The number of authors who published 10 or more articles in this field reached 20. In Fig. 4, the size of a node is proportional to the number of articles published by an author, the thickness of the line between nodes is proportional to the number of collaborative articles among authors, and different colors indicate the year of cooperation among authors. In the upper left corner of Fig. 4, we can see that the network density is only 0.0028, and the entire cooperative network is fragmented, indicating that the connections and cooperation between authors are not fixed and not close enough in this field of research.

2) INSTITUTIONAL DISTRIBUTION

Then, we used CiteSpace to generate an institutional collaboration network, as shown in Fig. 5, the name of the organization in the figure is abbreviated, for example, Univ means University. Table 2 lists the top 10 institutions with number of published articles. Among them, Massachusetts Institute of Technology (MIT) and Harvard University published 84 and 83 articles respectively, and they were the two organizations with the largest number of articles published. This is also reflected in Fig. 5, where the two nodes representing MIT and

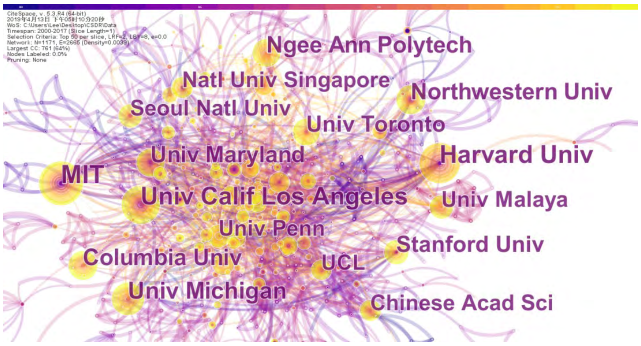

FIGURE 5. Institutional collaboration network in the field of chronic disease research driven by emerging technologies.

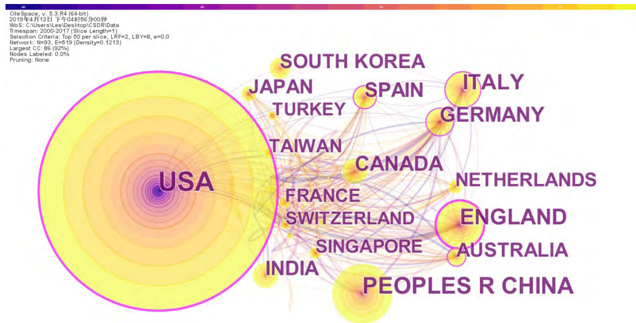

FIGURE 6. National collaboration network in the field of chronic disease research driven by emerging technologies.

TABLE 2. List of the top 10 institutions with number of published articles.

Institution	Number of published articles	LCS	GCS
MIT	84	396	2952
Harvard University	83	152	3719
University of California, Los Angeles	75	108	1557
University of Michigan	63	48	679
University of Maryland	58	160	1314
Northwestern University	57	165	1429
Columbia University	55	40	578
Ngee Ann Polytechnic	55	215	916
Stanford University	51	150	1732
Seoul National University	49	28	447

Harvard University are the largest of all nodes. The 10 institutions listed in Table 2 have published at least 50 articles, indicating that the field has received extensive attention from universities and academic institutions around the world.

The LCS and GCS in Table 2 represent the local citation score and the global citation score, respectively. LCS refers to the frequency with which an article is cited in the current database, and GCS refers to the frequency with which an article is cited in the Web of Science database [33]. As mentioned above, MIT and Harvard University not only ranked the best in the number of articles published, but also LCS and GCS. As everyone knows, these two universities are world-renowned top institutions of higher education with lofty status and academic influence. This is also reflected in this article, in the field of chronic disease research driven by emerging technologies, MIT and Harvard University also showed strong academic creativity. Although the University of Michigan has published 63 articles, ranking 4th, its LCS and GCS are significantly lower than those of the University of Maryland and Northwestern University. This shows that in this field, the articles published by the University of Michigan are not sufficiently influential and the quality of the articles is not high enough.

Strengthening cooperation between institutions is an important measure to improve the overall research capacity of the organization, complement the advantages of scientific research resources, and strengthen knowledge sharing. In addition, the level of cooperation between research institutions is one of the indicators for evaluating the status of research in a particular field. As shown in Fig. 5, the size of a node is proportional to the number of articles published by an institution, the thickness of a line between nodes is proportional to the number of collaborative articles between institutions, and different colors indicate the year of cooperation between institutions. It can be seen from Fig. 5 that there are more connections between institutions and they are close to forming a close network, which indicates that the cooperation between different institutions in this research field is extensive and close.

TABLE 3. List of the top 10 countries/regions with number of published articles.

Countries/ Regions	Number of published articles	Centrality	LCS	GCS
USA	1794	0.35	2576	34729
People's Republic of China	482	0.01	366	4853
England	403	0.17	489	7467
Italy	333	0.17	465	4426
Germany	252	0.23	225	4324
Canada	245	0.09	249	4274
India	230	0.01	172	1632
Spain	222	0.13	234	2601
South Korea	203	0	196	1744
Australia	183	0.16	180	2866

3) NATIONAL DISTRIBUTION

Finally, we analyzed the countries/regions that published relevant scientific articles in this field and generated a national collaboration network, as shown in Fig. 6. The size of the nodes in the graph is proportional to the number of articles published in the country or region, the width of the connection line between each node is proportional to the number of articles completed by the cooperation between countries or regions, different colors indicate the year in which the country or region cooperates to publish an article. The density of the network reached 0.0994, showing that numerous collaborations occur among countries or regions and that connection is extremely close. Table 3 lists the

FIGURE 7. Articles in the co-citation network in the field of chronic disease research driven by emerging technologies.

FIGURE 8. Co-citation time zone chart (year per slice is 3).

relevant information of the top 10 countries or regions with number of published articles. Whether in the figure or in the table, it is obvious that in terms of the number of articles published in this field of study, the United States stands out, far ahead of any other country in the world. The United States has published 1,794 articles in this field of research, which is more than the total number of papers published in the next five countries (the People's Republic of China, the United Kingdom, Italy, Germany, Canada). The United States is also outstanding in the three aspects of centrality, LCS and LGS, ranking first in the world. Centrality refers to how important a node is relative to other nodes. Although the People's Republic of China ranks second in terms of the number of articles, it is mediocre in terms of centrality, LCS and GCS, which indicates that the quality of papers published in China is not high enough and has little influence.

IV. LITERATURE CO-CITATION ANALYSIS

In this chapter, we mainly analyze the co-citations of literature and draw a literature co-citation network as shown in Fig. 7. The literature co-citation network refers to the knowledge network formed by two scientific documents simultaneously cited by the third or other literature [34]. In other words, an article has the same reference as another article, and the more documents that are cited together, the greater the relevance of the two articles, the closer the relationship and the similar academic background [35], [36].

The theories, models, and laws of the scientific community may become paradigms of a certain period of time and a certain research field. The scientific paradigm can provide a common set of rules and theoretical frameworks for a particular field of study [37], [38]. For example, when certain articles are repeatedly quoted by peers, then we can think that the knowledge described in this article is generally recognized by the scientific community, that is, a scientific paradigm is formed [39]. So, in order to see this paradigm relationship more intuitively, we analyzed the literature co-citation network. In accordance with Kuhn's historicist scientific development model, the paradigm refers to a set of beliefs, traditions, or theories that are collectively recognized by the scientific community during a certain historical period [40].

Each node in Fig. 7 represents a co-cited document, the size of the node is proportional to the frequency of the reference, and the width of the connection between the nodes is proportional to the number of times the two articles are referenced together. In the literature co-citation network, Chang and Lin [41] published an article entitled "LIBSVM: A Library for Support Vector Machines", which obtained the highest number of co-citations, reaching 138 times. Chang and Lin [41] is connected to Cuingnet *et al.* [42], Stonnington *et al.* [43], Vemuri *et al.*[44], and so on. If the connection between the two nodes is thicker, the links between the two articles are more closely related, the correlation is stronger, and the research objects are similar. The density of the network is only 0.0056, so in general, in the field of chronic disease research driven by emerging technologies, the co-citation network of literatures is relatively scattered and has not yet formed a mature co-citation network system.

CiteSpace was then used to generate the co-citation time chart shown in Fig. 8. In the figure, an important scientific literature is displayed with an intermediate centrality. It is clear from Fig. 8 that the distribution of the main scientific literature in different periods can be seen, and important scientific literature is mainly concentrated in 2006-2015. The literature research before 2006 is not yet mature, and the literature after 2015 has not been unanimously recognized by the peers, and the influence is still lacking.

V. ANALYSIS OF RESEARCH FOCUS

Research hotspots refer to the focus and hotspots of academic research in a certain period of time. The main manifestation is that a large number of literatures, theory, ideas and research groups have emerged in a certain field or discipline [45]. The development of science generally has the characteristics of alternating the traditional scientific and scientific revolutions [46]. A scientific revolution brings changes, and incommensurability exists between old and new paradigms; such incommensurability, i.e., the lexical system between old and new paradigms, will change accordingly; thus, the occurrence of a scientific revolution can be determined based on whether vocabulary has changed during that period [47]. Statistics the

TABLE 4. List of the top 10 keywords with the corresponding frequency.

	Keyword	Frequency	Centrality
1	stroke	589	0.11
2	classification	540	0.32
3	Alzheimer's disease	340	0.22
4	rehabilitation	323	0.28
5	diagnosis	323	0.13
6	robotics	318	0.12
7	artificial neural network	315	0.12
8	disease	304	0.13
9	support vector machine	276	0.01
10	machine learning	275	0.03

number of co-occurrences of keywords in scientific literature, the frequency of which can reflect the size of association between keywords, and the popular issues in this area of research in a particular period. Therefore, the keyword co-occurrence analysis included in the co-word analysis method can determine the research structure and hotspots in a particular field. Co-word analysis mainly means that when two professional terms (such as subject terms or keywords) that can express the research direction of a subject appear in the literature at the same time, there is a certain relationship between them, and the more times there are at the same time, the more intimate the relationship between the two words [48].

Keywords are highly concise and general about an article; they are the core and essence of an article. High-frequency keywords are often used to identify popular topics in a research field. That is, the main research content of a paper, even the overall research situation in a field, can be intuitively determined by analyzing keywords. Table 4 lists the top 10 keywords with the corresponding frequency. The highest frequency of occurrence of the keywords in Table 4 is "stroke", stroke is an acute cerebrovascular disease caused by a sudden rupture of the cerebral blood vessels. It can also refer to damage to the brain tissue caused by blood flow to the brain due to clogged blood vessels. Stroke, which is a common chronic disease, has a high morbidity incidence, high disability rate, and high mortality [49]. Stroke is largely attributed to hypertension, a common chronic disease that is an important controllable risk factor for stroke [50]. In general, the keywords with higher frequency in Table 4 can be roughly divided into three categories, the first category: keywords related to chronic diseases (such as stroke, Alzheimer's disease, obesity), the second category: keywords related to emerging technologies (e.g., artificial neural networks, support vector machines, machine learning), and the third category is research methods (such as classification, prediction).

The co-word network refers to constructing a co-word matrix by using keywords in the literature and its co-occurrence relationship, and then visually generating a co-word network diagram to reveal the research hotspots, development trends and knowledge structure evolution of a certain field or discipline [51]. Similarly, in terms of keyword

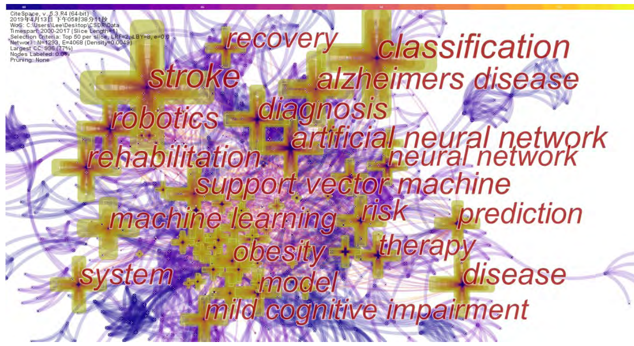

FIGURE 9. Keyword co-occurrence network in the field of chronic disease research driven by emerging technologies.

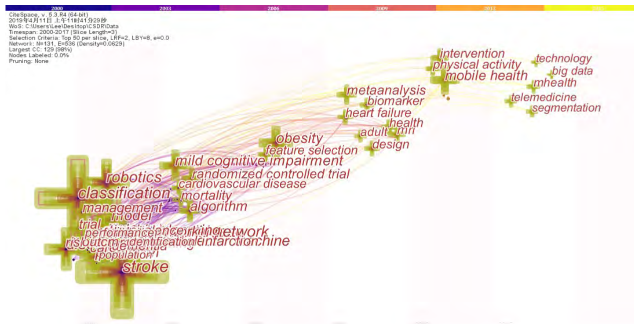

FIGURE 10. Keyword time zone chart (year per slice is 3).

analysis in this study, we use CiteSpace to generate a keyword co-occurrence network, as shown in Fig. 9. Each node in Fig. 9 represents a keyword, and the larger the node, the more frequently the keyword appears, and the connection between the nodes represents the co-occurrence relationship between the keywords. The co-word network density reached 0.0263, in summary, there is a strong connection between keywords, and the co-occurrence relationship is relatively close, indicating that the research results published in the field of chronic diseases research driven by emerging technologies are mostly multi-topic.

Finally, we introduced the keyword time zone chart to explore the evolution of keywords in 18 years, as shown in Fig. 10. It can be seen that many high-frequency keywords have been proposed in the early years, especially the top 10 keywords in Table 4 have appeared in 2000-2003, even earlier. It is worth noting that obesity began to receive attention in this field until around 2006. And scholars in this field did not begin research on mobile health until around 2012. Mobile health refers to the use of mobile communication devices (such as mobile phones, tablets computers, etc.) and wearable devices (such as smart watches, smart bracelets, etc.) to collect community and clinical health data, to provide medical information to doctors, researchers and patients, and to monitor patient vital signs in real time or provide care directly (via mobile telemedicine) [52]. From the figure we can also see the research hotspots in recent years, including: big data, mobile health, telemedicine, physical activity and so on. Telemedicine refers to the use of telecommunications and information technology to provide clinical care [53]. Physical activity is closely related to health, lack of physical activity may have a series of negative consequences for health, but appropriate physical activity can improve physical and mental health [54].

VI. CONCLUDING REMARKS AND FUTURE TRENDS

This study mainly discusses the time distribution, spatial distribution, literature co-citation and research focus of chronic disease research driven by emerging technologies knowledge. In terms of time distribution, the number of articles published and scholars in the field are increasing every year, and the growth trend in recent years is more obvious, almost linear growth. For spatial distribution, the author's cooperative network has a low density and a loose cooperative relationship. In contrast, cooperation between institutions and countries or regions is more extensive and closer. The literature co-citation network is relatively scattered and has not yet formed a mature co-citation network system. Finally, there is a strong connection between keywords, and the co-occurrence relationship is relatively close, the research results published in the field of chronic diseases research driven by emerging technologies are mostly multi-topic. This study revealed the development status of research in the field of chronic disease research driven by emerging technologies, analyzed and discussed the research hotspots and future development trends in this field, and provided important knowledge support for researchers in this field to carry out follow-up research.

Nowadays, emerging technologies are booming, and opportunities and challenges in the field of chronic disease research driven by emerging technologies coexist. Some research in this field has also been introduced in this study. Their research generally applies emerging technologies to the field of chronic diseases. I believe that in the near future, emerging technologies such as wearable devices, mobile health, deep learning and health robots will become research hotspots in this field [55].

In recent years, the improvement of information and communication technologies and the connectivity provided by mobile Internet anywhere and anytime have played key roles in modern healthcare solutions. In this context, m-health provides medical services to overcome geographic, time, and organizational barriers [56]. Mobile smart healthcare based on IoT and intelligent wearable device technology is becoming an important direction in the future of the e-health field. Wearable devices have shown great potential in postoperative recovery of heart disease patients and counseling for diabetes patients [57]. Most of the health-related information is obtained by sensing technology and wearable technology, which also forms the basis of health informatics. Sensing technology can weave or integrate sensors into clothing, accessories, and living environments for health information, and can even be designed as electronic tattoos or printed directly on the skin for long-term health monitoring [58]. Mobile health refers to the use of small wireless computing or communication devices that can be carried around to realize the integration of health sensor terminals, mobile communication platforms, and health services [59]. Mobile smart healthcare platforms can provide dynamic data analytics and knowledge service to patients with chronic diseases through personalized health information services [60]. The use of intelligent wearable devices in the field of chronic disease research will be helpful in conveniently, quickly, efficiently, and accurately obtaining and transmitting data associated with patients' body and physiology. For example, such devices can monitor the changes in a patient's heart rate throughout the day and provides advice based on historical health data analysis results. Advanced terminal technologies (such as smart clothing) and cloud technologies (such as big data analytics in cloud computing) can serve humans reliably and intelligently. Accordingly, Chen *et al.* [61] proposed a wearable 2.0 medical system to improve the quality of next-generation medical systems.

Health robots will become another important topic in the field of e-health. Robotics relates to robot design, manufacture, and applications. Robotics technology can obtain the real-time status of patients with chronic diseases. For example, a robot can be deployed in the daily activity area or residence of a patient and the real-time situation of the patient can be captured and observed through the cameras or sensors of the robot. In addition, robots can also obtain detailed medical health data by connecting to the mobile health devices worn by patients and transmitting their data to a data analysis platform in real time. In case of a life-threatening condition or other emergencies, robots can trigger an emergency alarm. Some patients with chronic diseases are not only physically afflicted by their diseases, but also suffer from a certain degree of psychological impairment. In such cases, robots can communicate normally with patients, provide language comfort, relieve boredom, and remind patients to take their medicines on time. Patients can also intelligently control the switches of household appliances, such as TV sets, lights, and air conditioners, using robots. As the aging society continuously grows and labor costs rapidly increase, health robots demonstrate considerable potential in the future.

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