Artificial Intelligence in the Life Sciences 1 (2021) 100006

Contents lists available at ScienceDirect

Artificial Intelligence in the Life Sciences

journal homepage: www.elsevier.com/locate/ailsci

The development trend of artificial intelligence in medical: A patentometric analysis

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ARTICLE INFO

Keywords:
Patentometric
Social network analysis
Artificial intelligence
Medical

ABSTRACT

Despite the burgeoning development of artificial intelligence (AI) applied in the medical field, there have been little bibliometric and collaboration network researches on the patents related to this inter-disciplinary research domain. Patentometric and Social Network Analysis (SNA) are used to conduct the characterizations of patent applications and cooperative networks, mapping a holistic landscape related to the AI-medical field. Derwent Innovation Index database (DII) is adopted as the patent data source. The results indicate that the quantity of AI-medical-related patent applications has been increasing explosively since 2011. The United States of America (US) is both the foremost country developing related technologies and the primary target of patent filing by non-residents. The hotspot of the current research include medical image recognition, computer-aided diagnosis, disease monitoring, disease prediction, bioinformatics, and drug development, etc. Low density of the assignees cooperation network implies the slight patent collaboration. Companies and academic institutions are the friskiest innovation subjects in the AI-medical field. The geographical proximity has a positive influence on the patent collaboration because co-owned patents are concentrated on the institutes in the same nation. Domestic collaboration is the major collaborative pattern. The spatial agglomeration of trans-regional patent cooperation is fairly sparse, which requires a further escalation in knowledge circulation. It has practical significance to understand the developing situation and patent cooperation network in the AI-medical field, providing a reference for future strategy planning, development, and technological marketization.

1. Introduction

In recent ten years, Artificial Intelligence (AI) techniques have been booming globally, due to the accumulation of big data, innovation of algorithms, and improvement of the computer processing capacity. AI is already notably promoting the major progress of technology and industry, from autonomous vehicles to medical diagnosis to advanced manufacturing. In terms of the life and medical sciences field, AI techniques have broad applications, for instance, drug design [4,10,27], prediction of disease/drug risk [24], medical diagnosis [1,30], facilitating detection of cancer, medical image analysis [23,26,31], genomics, physiological parameter monitoring [2,6], and so on. These applications of AI techniques are expected to change the work pattern of doctors and complement traditional medical tools, availably enhancing the accuracy and efficiency of diagnosis.

The patent data is regarded as a unique resource for the study of technological change [14]. Based on the patentometrics analysis, it can investigate the technique development trend [18,45]. Meanwhile, the importance of the collaboration network in promoting knowledge production and diffusion has also been extensively studied [32,38], and collaborations can facilitate the improvement of research quality, resulting in more effective scientific production [34]. Many studies are concerned on the co-author networks [33], co-citation networks [20], co-word networks [39], international collaborations [21,37,38], and cross-institution collaborations [7], in publications (e.g. papers and journals), which adopt the social network analysis (SNA) to study the relationships involved in the networks. However, to our knowledge, there is no bibliometric and collaboration network analysis based on patents in this inter-disciplinary research field.

Therefore, the patentometric is applied to gain a comprehensive view of the AI-medical techniques, and predict the development trend. The patent application year, technology life cycle, geographical distribution, and the collaboration relations of assignees are delved deeper into the status of technological development. SNA is carried out to investigate the collaboration network formed between institutions that are engaged in the AI-medical field. The schematic diagram of patent analysis is exhibited in Fig. 1.

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https://doi.org/10.1016/j.ailsci.2021.100006
Received 27 April 2021; Received in revised form 14 June 2021; Accepted 30 June 2021
Available online 6 July 2021

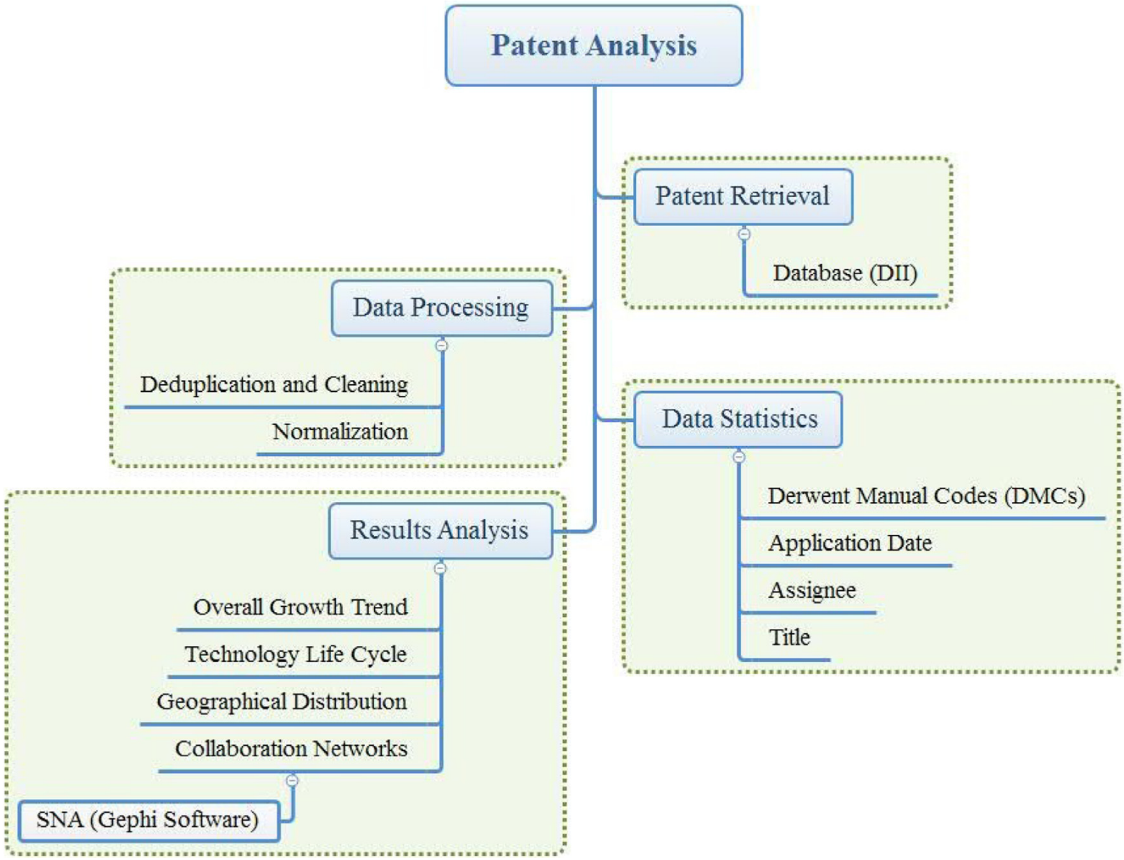

Fig. 1. Schematic research pathway of patent analysis.

Table 1
Search strategies used in Derwent Innovation Index [43].

Information	Data
Retrieval tactics	Topic: ("artificial intelligen*" or "depth learning*" or "deep learning*" or "natural language processing*" or "speech recognition*" or "computer vision*" or "gesture control*" or "smart robot*" OR "Video recognition*" OR "Voice translation*" OR "Image Recognition*" OR "machine intelligen*" or "Machine learning*") AND Derwent Manual Code: (B01* OR B02* OR B03* OR B04* OR B05* OR B06* OR B07* OR B08* OR B09* OR B10* OR B11* OR B12* OR B14* OR B15*)
Timespan	All years (1963–2019)
Date of retrieval	December 16, 2019
Results	1282 patent family records

2. Method and data

2.1. Data collection and pre-processing

The patent search strategies are presented in Table 1 [43], which consists of topic search and Derwent Manual Code (DMC) search. DMC is a hierarchical system of the DII database itself, providing a considerably detailed classification of technical subjects and the technical novelty of an invention [44]. According to the standard of DMCs, patents are divided into 21 sections (A to X, except I, O, R), and each section is subdivided into more specific classes. Section B (pharmaceuticals) is taken for the patent retrieval, which includes 15 subdivisions of the codes. 1282 records from Derwent Innovation Index (DII) database are retrieved and exported on December 16, 2019. Each record represents a patent family, a group of related inventions filed in one or multiple patent authorities [28]. Key elements of records include patent number(s), priority application information, DMCs, titles, designated states, application details, inventor(s), assignee(s), patent details, IPC classification number, cited patents, cited articles. Each of these patent family records is showed as a single patent. After manually removing duplicates, 3610 items of single patent information are acquired [43]. The data of assignees and patent quantity information is cleaned, grouped, and rearranged in an Excel spreadsheet.

2.2. Data analysis

The visualization software of Gephi and Tableau are employed for patent analysis. The patent cooperation network of the AI-medical field is carried out by the SNA method, using Gephi to view the relationships among network participants (assignees). Gephi is an open-source software based on the Java Virtual Machine (JVM), which can be used for the exploration of complex networks. In the network, the assignees correspond to the collaborative relationships, and the patent quantity denotes the weight given to the link between assignees. Each assignee is expressed as a node, and links between two nodes are regarded as the patent cooperation relationship. The structural features of the patent collaboration network are expressed by the SNA indicators, such as degree, density, and weighted PageRank.

The degree of a node is the number of connections incident upon it [16], which is a parameter to evaluate the significance of nodes in a network graph.

The density (*D*) of an undirected network is the ratio of the actual link quantity to the count of all possible links within the network, as shown in Eq. (1) [41].

$$D = \frac{L}{N(N-1)/2} \tag{1}$$

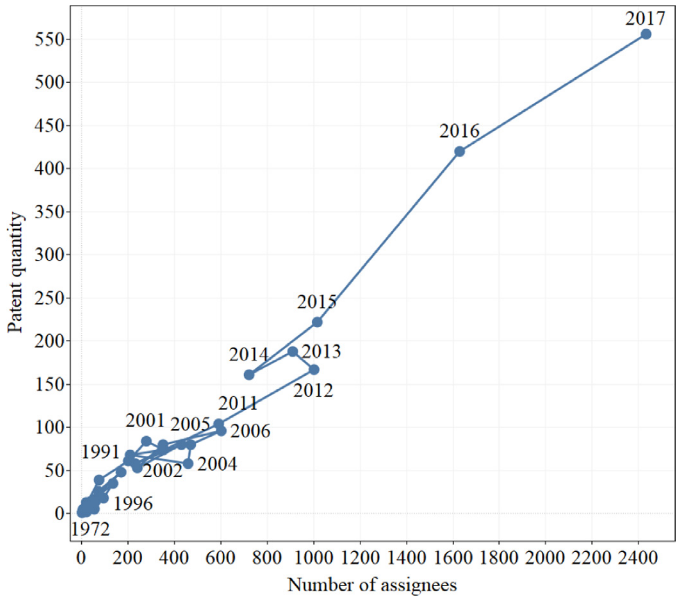

Fig. 2. Technology life cycle of AI-medical-related patents.

where L and N are the total amount of links and nodes in a network, respectively.

Weighted PageRank is a graph-based ranking algorithm to estimate the importance of the node by measuring the quantity and quality of links to a node [9]. The amount of Weighted PageRank is calculated as follows:

$$PR\_W(P_i) = (1-d)\frac{w(p)}{\sum_{i=1}^{N} w(p_i)} + d\sum_{i=1}^{k}\frac{PR(p_i)}{L(p_i)} \quad (2)$$

where $W(P_i)$ is the weight matrix for the nodes in the network; d is a damping factor that is set as 0.85 [46]; $L(P_i)$ is the amount of edges that is linked to P_i.

3. Results and discussion

3.1. Patent life cycle

Patent information can be employed to predict the tendency of industry development, especially in terms of market analysis and competition [29]. Patent life cycle, the change of cumulative patent amount via assignees, has been used as an S-curve to predict the technology development and life circle stage. Ernst [12] introduced four different development stages of the technology life cycle: (1) emerging; (2) growth; (3) maturity; and (4) saturation. As depicted in Fig. 2, the technology life cycle of AI-medical-related patents can be segmented into two phases: (1) Emerging period (from the year 1972 to 2010), the technology has experienced approximately 40 years of slow development. The AI-medical-related patents in the emerging stage merely occupy 30% of the total. (2) Growth period (from the year 2011 to 2017), the number of patents (assignees) rise rapidly in this stage, from 104 (590) in 2011 to 556 (2433) in 2017. The patents in 2018 and 2019 are excluded, as a result of the 18-month confidentiality period of patent applications.

The development phases of AI-medical-related patents are consistent with the history of AI techniques. Although the term “artificial intelligence” was coined at a Dartmouth conference in 1956, it experienced the twists and turns development progress over the subsequent forty years, commonly known as “AI summers and winters”. In 1997, an IBM computer called IBM’s Deep Blue, defeated the world chess champion in a six-game match. However, Deep Blue couldn’t do anything except playing chess. In 2011, IBM researchers utilized the open-domain question-answering (QA) system, nicknamed Watson, to compete on the

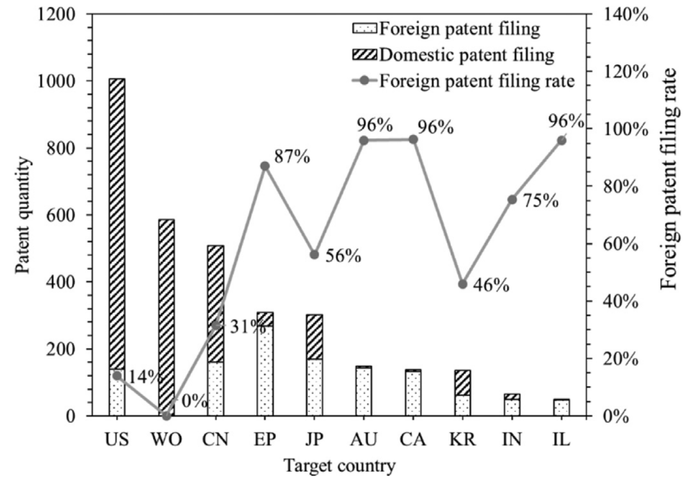

Fig. 3. Number of AI-medical-related patents filed by domestic and foreign in the top 10 countries or regions.

game of Jeopardy! Eventually, Watson prevailed over the two highest-ranked human players and obtained the victory. For general intelligence, Watson hits a symbolic milestone because it can comb through electronic medical records and the medical literature (e.g. journals), to make a clinical decision for human diseases [11,36]. This promotion results in a significant breakthrough in AI-medical technology development in a short term. After that, numerous enterprises or institutions initiate to invest in “Artificial Intelligence for Healthcare” from 2014, leading to a remarkable increase in the patent and assignee quantities.

3.2. Geographical distribution

The quantity of AI-related patents on the medical field by domestic and foreign countries or regions is presented in Fig. 3. Domestic patent fillings correspond to the patent applications that first field in the countries or regions; foreign patent fillings represent the subsequent filings (countries or regions of second filing). There is an obvious heterogeneity across countries or regions. Concerning the rate of total foreign patent filing, the top 5 countries/regions are in the following order: Australia (96%), Canada (96%), Israel (96%), Europe (87%), and India (75%). The result demonstrates that these five countries, their own national Research and Development (R&D) in the AI-medical field are of comparative weakness. By contrast, the US has the lowest rate of total foreign patent filing (14%), indicating its powerful R&D capability in the AI-medical field.

Looking at the number of total foreign patent filings, the country or region ranked first in the AI-medical field is European with 268 records, followed by Japan (169 records), China (160 records), Australia (143 records), and the US (140 records). These are the most popular foreign patent filing countries or regions in the field of AI-medical, standing for the major competitive markets in the globe.

3.3. Productive assignees

The top 25 assignees are demonstrated in Table 2, which together account for 23.40% of all patent applications in the AI-medical field. As shown in Table 2, companies are particularly active, making up about 72% of the top 25 holders. Other patent holders include 4 universities, 2 research institutions, and an individual.

There are 18 American organizations or individuals in the ranking, of which the leader is the University of California (Table 2). France is ranked second with 3 organizations on the list. The other four listed assignees are from Cayman Islands, Switzerland, German, and Netherlands, respectively. It is noticed that the top 25 assignees are all from the developed countries and regions. Cantner and Rake [5] also report

Table 2
Main assignees of AI-medical-related patents.

No	Assignee	Organization Type	Country/Region origin	Patent Quantity	Patent Cooperation Quantity	Partners
1	University of California	University	USA	79	42	3
2	Berg Pharma	Enterprise	USA	62	0	0
3	uBiome	Enterprise	USA	62	0	0
4	NantOmics	Enterprise	USA	61	0	0
5	Roche	Enterprise	Switzerland	54	13	3
6	IBM	Enterprise	USA	37	0	0
7	YouHealth	Enterprise	Cayman Islands	34	34	2
8	Philips	Enterprise	Netherlands	32	0	0
9	Pandya Ashish A	Individual	USA	32	0	0
10	Prometheus Lab	Enterprise	USA	32	7	1
11	AP-HP	Hospital	France	31	31	10
12	HeartFlow	Enterprise	USA	30	0	0
13	Gritstone Oncology	Enterprise	USA	29	0	0
14	CNRS	Research Institution	France	27	27	7
15	Circeca Theranostics	Enterprise	USA	26	13	3
16	INSERM	Research Institution	France	25	25	10
17	Sera Prognostics	Enterprise	USA	25	0	0
18	Yale University	University	USA	25	4	3
19	Eastern Virginia Medical School	University	USA	24	0	0
20	Intel	Enterprise	USA	24	0	0
21	Osio	Enterprise	USA	24	0	0
22	Stanford University	University	USA	24	2	3
23	Medtronic	Enterprise	USA	23	0	0
24	SIEMENS	Enterprise	German	23	0	0
25	Bio-Rad	Enterprise	USA	22	21	5

Table 3
Core patents of top 25 assignees.

Publication Number	Application dates	Title	Assignee
US9984201	2015–12–31	Method and system for determining cancer status	Youhealth
US10093986	2017–02–16	Leukemia methylation markers and uses thereof	Youhealth
US7666583	2005–01–18	Identification of cancer protein biomarkers using proteomic techniques	Yale University
US8975379	2009–12–22	Identification of cancer protein biomarkers using proteomic techniques	Yale University
US7790463	2006–02–02	Methods of determining whether a pregnant woman is at risk of developing preeclampsia	Yale University
US7873479	2006–11–30	Methods of diagnosing inflammatory bowel disease	Prometheus Lab
US7759079	2005–05–11	Methods of diagnosing inflammatory bowel disease	Prometheus Lab
US8463553	2007–08–20	Methods for diagnosing irritable bowel syndrome	Prometheus Lab
US8200599	2011–06–29	100 gbps security and search architecture using programmable intelligent search memory	Pandya Ashish A.
US9086580	2013–08–09	Contact lens use in the treatment of an ophthalmologic condition	Osio
CN104823100	2013–08–09	Contact lenses and methods of determining the fit of a contact lens for an eye of an individual	Osio
US7410763	2005–09–01	Multiplex data collection and analysis in bioanalyte detection	Intel
US10398386	2013–05–16	Systems and methods for estimating blood flow characteristics from vessel geometry and physiology	Heartflow
US10055540	2017–03–22	Neoantigen identification, manufacture, and use	Gritstone
CN103501859	2012–03–02	Probing analysis and its application based on cell	Berg

that the core of the network about scientific publications related to pharmaceutical research is dominated by high-income Organization for Economic Cooperation and Development (OECD) countries. This may be ascribed to the knowledge-concentrated characteristic of the pharmaceutical industry, with the highest investment R&D intensity [22].

In Table 2, the University of California is the leading institution with the largest number of patents (around 2.19% of total), followed by the Berg Pharma LLC. and uBiome Inc. (both with 62 patents). Innography platform is conducted to filter representative patents by the evaluation indicator of patent strength [17]. There are 110 items of core patents (patent strength≥90) in the AI-medical field. Table 3 lists the core patents of the top 25 assignees, and the whole patent information can be found in the supplementary material.

Most patents of the University of California contain claims for the utilization of biomarker (e.g. methylation) in various cancer, the method for predicting protein binding from primary structure data, disease monitoring. The patents of Berg Pharma LLC. and uBiome Inc. are focused on their independently developed system and platform. The former is used to analyze the biological process (e.g., disease condition, drug-induced toxicity condition); the latter is for analyzing a microorganism-related condition (e.g., human behavior condition, disease-related condition, etc.).

Regarding the quantities of partners and co-owned patent applications, the French public health agent of Assisance Publique-Hopitaux de Paris (AP-HP) holds the first place, of which the patents contain claims for the biomarkers combination for the prognosis of hepatic fibrosis or Hepatitis C Virus treatment. The AP-HP possesses 31 co-ownership patents with 10 co-assignees. The deeply multilateral cooperation of AP-HP might be in connection with its international strategy that develops larger-scale cooperation projects with other institutions, for the benefit of global health [3].

There are 14 assignees without co-ownership patents, in the top 25 assignees. The Berg Pharma LLC. (a clinical-stage, AI-powered biotechnology company), uBiome Inc. (a company providing microbiome testing services in the United States), and NantOmics LLC. (a molecular testing company), despite being the critical assignees, they do not have any technological partners in the AI-medical field. Among the top 25 assignees, Roche Inc., YouHealth Inc., Circeca Theranostics LLC., and Prometheus Laboratories Inc. are the only five companies that possess co-assigned patents with other organizations. The low patent cooperation rate of companies may be attributed to the potential knowledge leakage risks accompanied by collaboration, although companies collaborate with partners or co-opetitors can bring more opportunities for knowledge acquisition and generate technological breakthroughs [42].

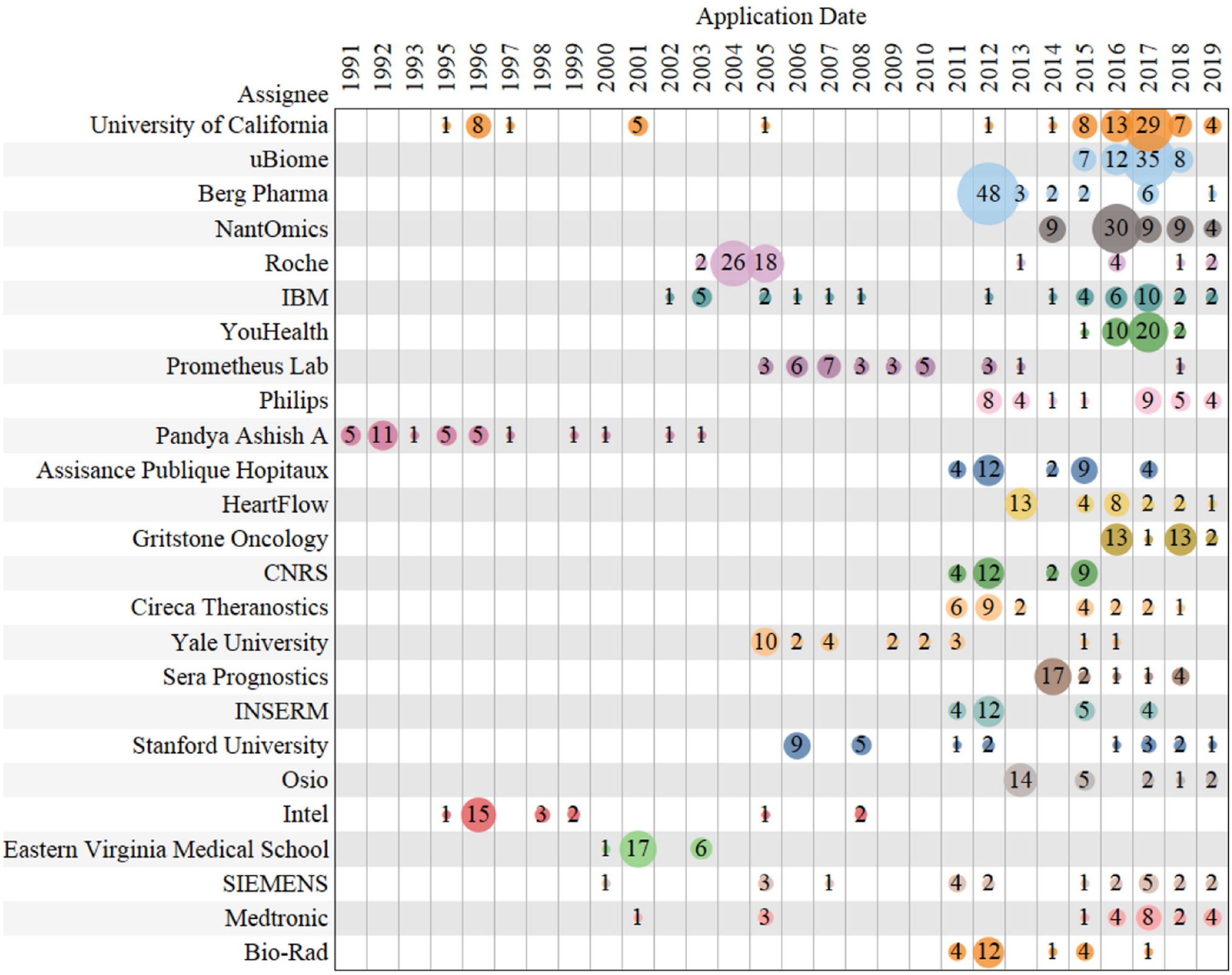

Fig. 4. Temporal evolution of patent applications for the top 25 assignees.

Thus, multinational corporations (MNCs) generally choose to establish overseas subsidiaries or overseas R&D laboratories, to source knowledge from the host location [35].

Fig. 4 exhibits the patent applications temporal evolution of the top 25 assignees. It can be seen that the patents of majority assignees have been filed mostly since 2011. For Pandya Ashish A, Intel, and Eastern Virginia Medical School, the patent applications are in the top ranks of quantity. Nevertheless, the patents of these assignees in the AI-medical domain are all filed before 2008, indicating the lack of subsequent researches.

3.4. Patents cooperation network

The collaboration network of patent assignees has been proven to evaluate what positions organizations occupy in a special technology field [8,25]. The SNA method is conducted to characterize the cooperative network of AI-medical-related patents, using the visualization tool Gephi. Fig. 5 shows the evolution of patent collaborative networks in the AI-medical field, the correlative network parameters are listed in Table 4. Each node stands for an assignee, of which the area has a positive correlation with the total patent quantity of the relevant assignee. The links represent the cooperative relationships among the AI-medical-related patents, of which the thickness demonstrates the collaboration strength between two assignees, that is, the quantity of co-ownership patents.

The low density of the AI-medical-related patent cooperative network (< 0.01) indicates the slight collaboration. The number of nodes and links is increasing, but the growth rate of nodes is higher than that of links, leading to a downward trend of density in the cooperative networks. Because AI technology in the medical field is still in a rapidly developing stage, and the cooperative groups are small and unstable.

To view the cooperative relation, Fig. 6 exhibits the collaboration network with nodes whose degrees are over one, excluding the location where a node without connection to other nodes. The color of nodes is related to the category of assignees.

Overall, 396 assignees participate in the technological collaborations, and 185 assignees occupy more than one external partner. The inter-organizational collaboration network is involved in 143 enterprises, 4 government departments, 12 hospitals, 19 research institutions, 66 universities, and 152 individuals. The corresponding main assignees are shown in Table 5. It can be seen that companies and individuals take the predominant positions in the network. Nevertheless, there are no obvious collaboration clusters in the collaboration network, which may be due to the fact that AI-medical-related technology is in the continued rapid development stage.

Table 6 exhibits the top ten assignees of AI-medical-related patents with high Degree and Weighted PageRank. It is observed that the AP-HP and French National Institute of Health and Medical Research (INSERM) simultaneously possess a high Weighted PageRank and a high Degree, demonstrating the greater importance and influence of them than other assignees in the AI-medical field.

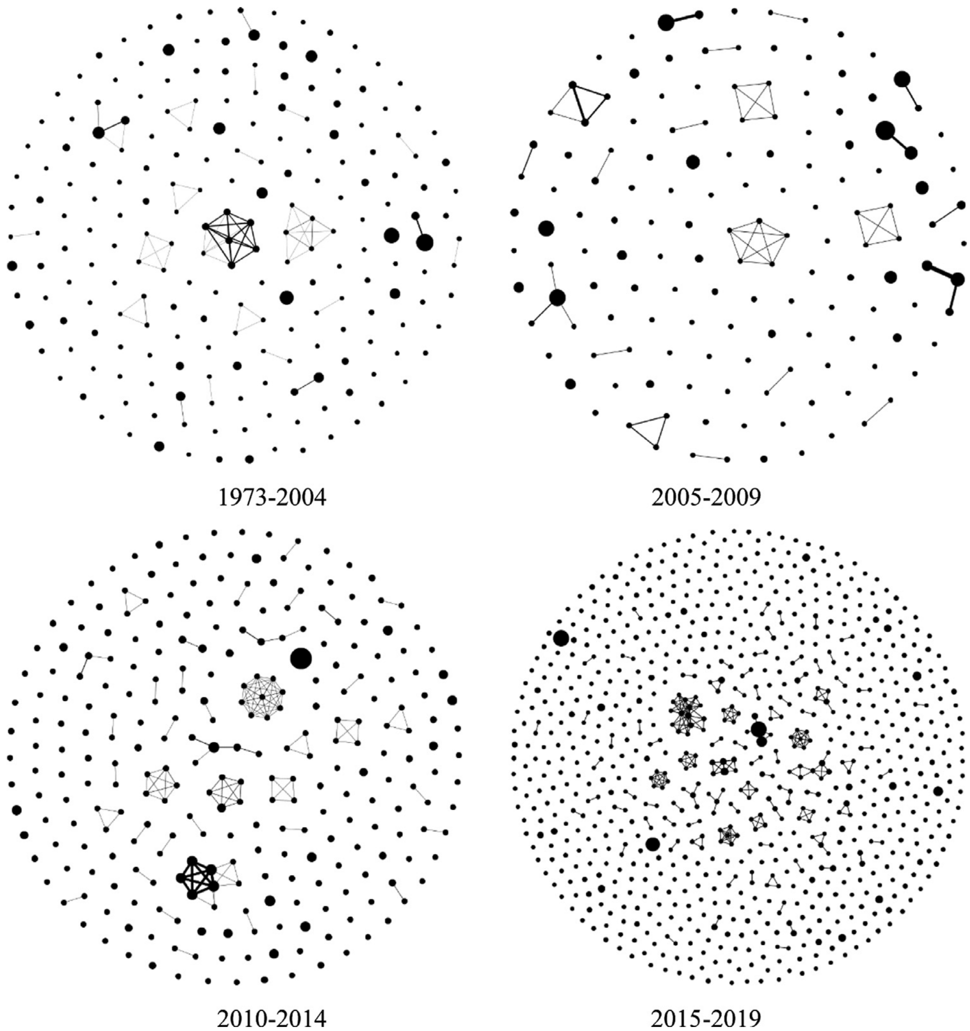

Fig. 5. Evolution of patent collaborative networks in the AI-medical field.

Table 4
Parameters of the collaborative network from 1973 to 2019.

Periods	Node	Edge	Average Degree	Network Density	Network Diameter
1973–2004	208	68	0.654	0.003	2
2005–2009	145	48	0.662	0.005	2
2010–2014	271	132	0.974	0.004	3
2015–2019	829	265	0.639	0.001	4

Table 5
Top 10 assignees for patent applications in the AI-medical field.

No	Enterprise	NOP[1]	Individual	NOP	Research Institution	NOP	University	NOP
1	uBiome	62	Pandya Ashish A	32	Prometheus Lab	32	University of California	79
2	Berg Pharma	62	Zhou Tiger	20	CNRS	27	Yale University	25
3	NantOmics	61	Fernandez Dennis	19	INSERM	25	Stanford University	24
4	Roche	54	Zhou Andrew	14	Hudsonalpha Institute For Biotechnology	12	Eastern Virginia Medical School	24
5	IBM	37	Randox	13	Cdx Lab	11	Harvard University	22
6	YouHealth	33	Ben Hador David	11	Agency For Science Technology & Research Astar	7	Columbia University	21
7	Philips	32	Pachmann Ulrich	11	London Health Sciences Centre Research	6	Case Western Reserve University	12
8	HeartFlow	30	Pachmann Katharina	11	Fred Hutchinson Cancer Research Center	5	Chinese University of Hong Kong	12
9	Gritstone Oncology	29	Dugas Martin	9	Cleveland Clinic	5	Ludwig Maximilians University Munich	11
10	Cireca Theranostics	26	Haferlach Torsten	9	National Cancer Center	4	MIT	10
			Tian Ge	9	Korea Advanced Institute of Science & Technology	4	Seoul National University	10
			Kern Wolfgang	9	Parkland Center for Clinical Innovation	4		
			Yee Richard W	9	Industrial Technology Research Institute	4		
			Kolhmann Alexander	9	Chinese Academy of Sciences	4		

[1] NOP: Number of Patents.

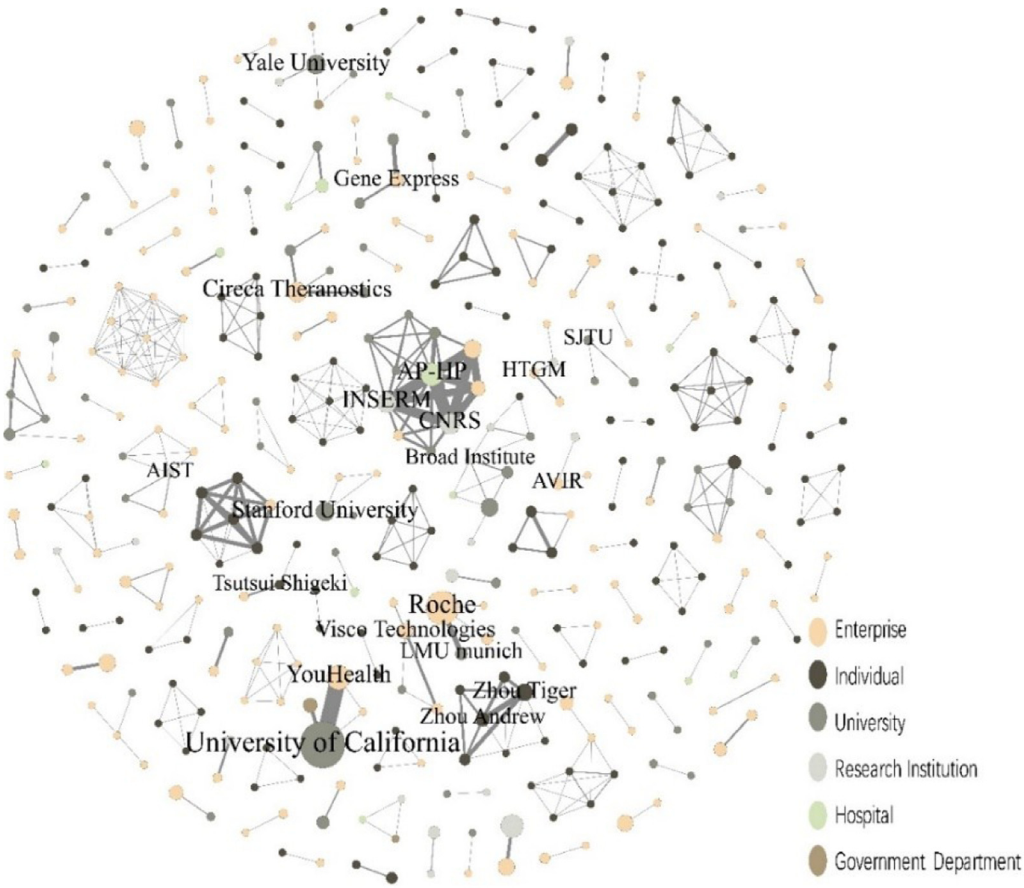

Fig. 6. Main cooperative network of AI-medical-related patents (degree≥1)
AP-HP: Assisance Publique-Hopitaux de Paris; AIST: National Institute of Advanced Industrial Science and Technology; HTGM: HTG Molecular Diagnostics; LMU: Ludwig Maximilians University; SJTU: Shanghai Jiao Tong University.

Table 6
Top 10 assignees with high Degree and Weighted PageRank.

No	Assignee	Category	Degree	No	Assignee	Category	Weighted PageRank
1	AP-HP	Hospital	10	1	AH–HP	Hospital	0.003890
2	INSERM	Research Institution	10	2	Zhou Tiger	Individual	0.003698
3	VAREC	Enterprise	8	3	Roche	Enterprise	0.003681
4	Abacus Innovations Technology	Enterprise	8	4	Circea Theranostics	Enterprise	0.003671
5	Reveal Imaging Technologies	Enterprise	8	5	Yale University	University	0.003570
6	QTC Management	Enterprise	8	6	University of California	University	0.003544
7	Systems Made Simple	Enterprise	8	7	INSERM	Research Institution	0.003352
8	SYTEX	Enterprise	8	8	Visco Technologies	Enterprise	0.003303
9	OAO	Enterprise	8	9	Broad Institute	Enterprise	0.003281
10	Lockheed Martin Industrial Defender	Enterprise	8	10	AVST	Research Institution	0.003170

The AP-HP also has the most partners and co-owned patent applications. This French medical institution owns 31 cooperation patents together with 10 co-assignees, including two French research institutions (CNRS-Center National de la Recherche Scientifique, and INSERM), five French universities, two US enterprises (Ariana Pharma Inc., and Bio-Rad Inc.), and one U.K. enterprise (Heron International). Around 70 percent cooperators of AP-HP are from France. For the University of California, this US university has filed 42 cooperation patents with three companies that are YouHealth Inc. (the US, 34 patents), Lawrence Livermore National Security, LLC (the US, 8 patents), and Guangzhou Youze Biotech Inc. (China, 1 patent), respectively. Nearly all of its co-owned patents are in partnership with US companies in the AI-medical field. Results suggest that the geographical location of partners plays a significant role in inter-organizational collaboration. Enterprises and academic institutions locating in the same geographic region, cooperate more closely in terms of patents. Domestic collaborations have a major implication for firm innovation [19]. Guellec and van Pottelsberghe [15] find that countries, blessed with geographical proximity and technological proximity, are more liable to collaborate. This is owing to the lower distance among the cooperators, the higher likelihood of frequent interactions among them [42]. Even if the influence of geography factor has reduced recently, because of the rapid growth of internet and transportation networks [13]. Therefore, the spatial agglomeration of trans-regional patent cooperation in the AI-medical field needs to be further strengthened to accelerate the circulation of knowledge.

3.5. IPCs co-occurrence network

The IPC co-occurrence network can be utilized to reveal novel convergence patterns [40]. Fig. 7 shows the IPCs co-occurrence network of

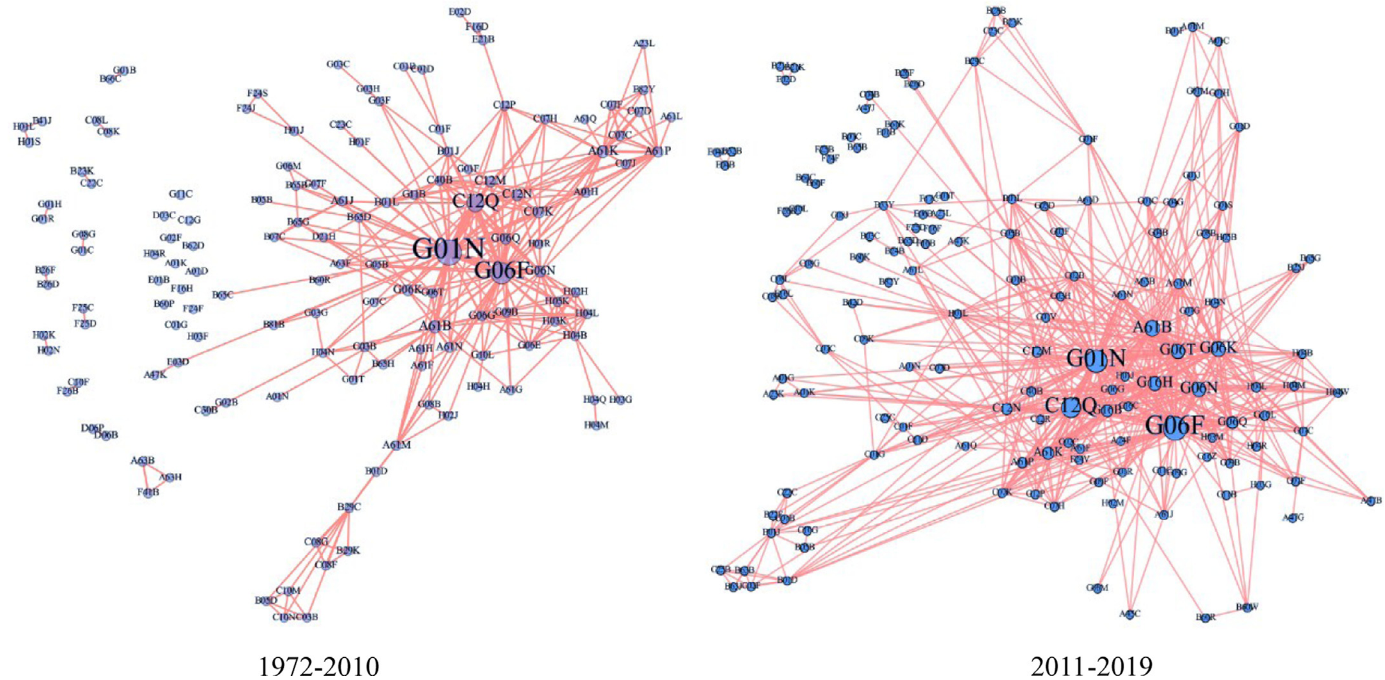

Fig. 7. IPCs co-occurrence network of AI-medical-related patents.

Table 7
Top 20 IPCs of AI-medical-related patents.

1972–2010					2011–2019				
No	IPC	Frequency	Degree	PageRank	No	IPC	Frequency	Degree	PageRank
1	G01N	473	37	0.094844	1	G06F	721	57	0.070316
2	G06F	357	33	0.067699	2	G01N	644	61	0.084289
3	C12Q	239	24	0.050388	3	C12Q	519	31	0.058841
4	A61B	99	19	0.025953	4	A61B	337	49	0.042702
5	A61K	82	20	0.021537	5	G06K	293	47	0.042102
6	G06N	67	19	0.02273	6	G06N	280	35	0.036697
7	C07K	63	12	0.017223	7	G06T	259	30	0.033535
8	C12N	62	11	0.018162	8	G16H	241	33	0.036397
9	C12M	56	12	0.01871	9	A61K	164	30	0.024917
10	G06Q	49	14	0.015439	10	G16B	153	22	0.021886
11	G06K	47	12	0.009135	11	G06Q	139	31	0.017608
12	A61P	45	16	0.016056	12	C12N	130	28	0.021812
13	A61M	32	10	0.006691	13	C12M	86	24	0.013107
14	B01J	32	8	0.011515	14	A61P	73	16	0.010357
15	C40B	31	16	0.010851	15	A61M	68	18	0.009575
16	B01L	31	8	0.012352	16	C40B	43	15	0.008514
17	A61J	29	9	0.011245	17	G06G	41	11	0.011459
18	G06G	29	14	0.010834	18	G10L	40	18	0.0099
19	A61N	27	7	0.010606	19	H04L	35	17	0.008081
20	G06T	24	9	0.007821	20	A61F	32	5	0.006322

two periods (1972–2010 and 2011–2019), and the Force Atlas algorithm is adopted in the layout.

Each node stands for an IPC, and the links represent the co-occurrences of IPCs in one patent. The nodes with higher frequency are located in the center of the IPCs co-occurrence network. It can be seen that the rapid development of AI technology brings about a larger-scale of IPCs co-occurrence network in the recent decade. The network density increases from 0.033 (1972–2010) to 0.053 (2011–2019).

The frequency, degree and PageRank of main IPCs are exhibited in Table 7. Compared to the period of 1972–2010, there is five new high-frequency IPCs appeared in 2011–2019, which respectively are G16H (healthcare informatics), G16B (bioinformatics), G10L (speech analysis or synthesis; speech recognition; speech or voice processing; speech or audio coding or decoding), H04L (transmission of digital information), A61F (filters implantable into blood vessels; prostheses; devices providing patency to, or preventing collapsing of, tubular structures of the body). Furthermore, G06K (recognition of data) slips from 11th to 5th rank, and G06T (image data processing or generation) moves up from 20th to 7th place in the rankings. The PageRank of these two IPCs has increased by nearly three times over the past ten years, revealing that the focus in 2011–2019 is G06K and G06T.

Table 8 lists the primary IPCs co-occurrence relation of AI-medical-related patents. G01N (investigating or analyzing materials by determining their chemical or physical properties) and C12Q (measuring or testing processes involving enzymes, nucleic acids or microorganisms; compositions or test papers therefore; processes of preparing such compositions; condition-responsive control in microbiological or enzymological processes) are the most frequent IPCs co-occurrence association in the two periods. Compared to the period of 1972–2010, the new IPCs associations in 2011–2019 can be contributed to find out the emerging

Table 8
Top 20 IPCs technology convergence of AI-medical-related patents.

1972–2010			2011–2019		
No	IPCs Association	Frequency	No	IPCs Association	Frequency
1	G01N-C12Q	170	1	G01N-C12Q	210
2	G06F-G01N	152	2	G06N-G06F	128
3	G06F-C12Q	105	3	G06F-C12Q	121
4	G01N-A61B	76	4	G06T-G06K	113
5	G06N-G06F	63	5	G06F-G01N	112
6	G01N-C12N	56	6	C12Q-C12N	72
7	G01N-C12M	47	7	G06N-G06K	64
8	A61P-A61K	45	8	G16B-C12Q	58
9	C12Q-C12M	44	9	A61P-A61K	55
10	G01N-C07K	43	10	G16H-G01N	55
11	C12Q-C12N	43	11	G06T-G01N	55
12	G06Q-G06F	34	12	G01N-A61B	54
13	G06N-G01N	34	13	G16H-A61B	53
14	G06F-C12M	33	14	G06K-G06F	53
15	G06Q-G01N	31	15	G06F-A61B	52
16	G01N-B01L	31	16	G16B-G01N	52
17	G06F-C07K	30	17	G06N-A61B	52
18	G06F-C12N	26	18	G06T-A61B	50
19	A61N-A61B	24	19	G06K-A61B	49
20	G06F-A61B	24	20	G16H-G16B	47

trends, e.g. G06T-G06K (AI in medical image recognition), G06N-G06K (AI in medical diagnostic system), G16B-C12Q (prediction of enzyme activity), etc. The results suggest that the application of AI technologies in the medical field mainly focuses on medical image recognition, computer-aided diagnosis, disease monitoring, disease prediction, bioinformatics, and drug development, etc.

4. Conclusion

The study systematically investigates the development trend and technical cooperation of AI techniques in the medical field, through the patentometric and SNA method. The results demonstrate that numbers of AI-medical-related patent applications have been in a period of rapid growth since 2011, which is attributable to the breakthrough progress of artificial intelligence algorithms and the accumulation of big data. America is both the significant technical innovation country in the AI-medical field and the primary competitive market. The main applications are medical image recognition, computer-aided diagnosis, disease monitoring, disease prediction, bioinformatics, and drug development, etc. The active and key players in the AI-medical domain are companies and academic institutions. Furthermore, the geographical location of institutions influences patent cooperation, and the major collaborative pattern is domestic collaboration.

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.

Acknowledgments

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. An earlier version of this paper was presented as a poster paper at 18th International Conference on Scientometrics & Informetrics.

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