Original Article

Global trend in research of intracranial aneurysm management with artificial intelligence technology: a bibliometric analysis

Fujunhui Zhang[1,2]^, Mirzat Turhon[1,2], Jiliang Huang[1,2], Mengxing Li[1,2], Jian Liu[1,2], Yisen Zhang[1,2], Ying Zhang[1,2]^

[1]Department of Interventional Neuroradiology, Beijing Neurosurgical Institute, Capital Medical University, Beijing, China; [2]Department of Neurosurgery, Beijing Tiantan Hospital, Capital Medical University, Beijing, China

Contributions: (I) Conception and design: F Zhang, M Turhon; (II) Administrative support: Y Zhang; (III) Provision of study materials or patients: None; (IV) Collection and assembly of data: F Zhang, M Turhon; (V) Data analysis and interpretation: F Zhang; (VI) Manuscript writing: All authors; (VII) Final approval of manuscript: All authors.

Correspondence to: Ying Zhang, MD. Department of Interventional Neuroradiology and Department of Neurosurgery, Beijing Neurosurgical Institute and Beijing Tiantan Hospital, Capital Medical University, Nansihuan Xilu 119, Fengtai District, Beijing 100070, China. Email: yingzhang829@163.com.

Background: The use of artificial intelligence (AI) technology has been growing in the management of intracranial aneurysms (IAs). This study aims to conduct a bibliometric analysis of researches on intracranial aneurysm management with artificial intelligence technology (IAMWAIT) to gain insights into global research trends and potential future directions.

Methods: A comprehensive search of articles and reviews related to IAMWAIT, published from January 1, 1900 to July 20, 2023, was conducted using the Web of Science Core Collection (WoWCC). Visualizations of the bibliometric analysis were generated utilizing WPS Office, Scimago Graphica, VOSviewer, CiteSpace, and R.

Results: A total of 277 papers were included in the study. China emerged as the most prolific country in terms of publications, institutions, cooperating countries, and prolific authors. The United States garnered the highest number of total citations, institutions with the highest citations/H index, cooperating countries (n=9), and 3 of the top 10 cited papers. Both the total number of papers and the citation count exhibited a positive and significant correlation with the gross domestic product (GDP) of countries. The journal with the highest publication frequency was Frontiers in Neurology, while Stroke recorded the highest number of citations, H-index, and impact factor (IF). Areas of primary interest in IAMWAIT, leveraging AI technology, included rupture risk assessment/prediction, computer-assisted diagnosis, outcome prediction, hemodynamics, and laboratory research of IAs.

Conclusions: IAMWAIT is an active area of research that has undergone rapid development in recent years. Future endeavors should focus on broader application of AI algorithms in various sub-fields of IAMWAIT to better suit the real world.

Keywords: Artificial intelligence (AI); intracranial aneurysm (IA); management; bibliometric analysis

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^ ORCID: Ying Zhang, 0000-0002-5812-372X; Fujunhui Zhang, 0000-0001-8735-5979.

Introduction

Intracranial aneurysm (IA) is a prevalent cerebrovascular disease, affecting 3% to 7% of the adult population (1,2) and is associated with a potentially fatal subarachnoid hemorrhage (SAH) leading to high mortality and disability rates (3). Despite advancements in IA management, including diagnosis, rupture risk assessment, treatment option selection, and follow-up observation, it remains heavily dependent on individual clinician experience. The multifaceted challenges associated with aneurysm management cannot be resolved with conventional approaches.

Artificial intelligence (AI) is an algorithmic technique that automates intellectual tasks and has demonstrated favorable performance in various medical fields (4). Recently, AI technology has shown promising results in the management of early neurological diseases and is anticipated to provide clinicians with guidance, resulting in higher accuracy and efficacy at all stages of IA management (5,6).

Bibliometric analysis entails the enumeration and statistical analysis of scientific output, encompassing articles, publications, citations, patents, and more complex indicators, to assess the contributions of authors, journals, institutions, or countries and identify trends in recent research directions (7,8). The application of bibliometric analysis has gained increasing popularity among clinical disease researchers. Zhang *et al.* (9) conducted a bibliometric analysis of 5,406 articles on IAs published between 2012 and 2021, while Lu *et al.* (10) evaluated the nature, content, and temporal changes of the 100 most cited articles on unruptured aneurysms. By comprehending the origins and designs of IA articles, we can better anticipate the future state of this field. However, to the best of our knowledge, no up-to-date bibliometric analysis study has been published to date on the application of IA management with AI technology (IAMWAIT).

This study aims to perform a bibliometric analysis of articles retrieved from IAMWAIT and reveal the most influential or prolific countries, institutions, journals, authors, co-cited papers, co-cited references, and potential collaborators. Through keyword analysis and reference cluster analysis, the major research directions and frontiers in this field have been detected.

Methods

From January 1, 1900 to July 20, 2023, we conducted a literature search using the Web of Science Core Collection (WoSCC) database. Two researchers screened the publications separately (Fujunhui Zhang and Mirzat Turhon) and the disputes were resolved by a senior researcher (Ying Zhang) after a collaborative discussion.

The bibliometric parameters of publications were extracted, including title, publishing date, country, author, institution, journal, keywords, and references. WPS Office 2022.11.03 (Kingsoft Office, Beijing, China) was used for the analysis of contribution. Scimago Graphica (Version 1.0.25) was used to generate the collaborative map of countries. VOSviewer (Version 1.6.18) was used for network visualizations while CiteSpace (Version 6.2.4) was used for cluster analysis, dual-map overlay of citations, timeline, and strongest citation bursts of references or keywords. R (Version 4.0.3) was used to generate the thematic map and thematic evolution analysis based on the "Bibliometric" package.

The concept of relative research interest (RRI) can be defined as the ratio of the number of publications pertaining to IAMWAIT in a given year to the total number of publications on IA within the WoSCC database for the same period, as outlined in reference (9). Meanwhile, the metric of average paper citations refers to the quotient of the total number of citations received by a given set of articles and the number of articles included in that set. To account for fluctuations in publication trends over time, the gross domestic product (GDP) of each country was calculated by aggregating data from 2006 to 2022. The H-index, which measures the number of publications that have received citation counts of at least H, was determined for the IAMWAIT field during the period spanning from 2006 to 2022, as described in reference (11).

Results

General data

The comprehensive literature search yielded a total of 504 publications, which underwent a rigorous screening process. Among these, 36 publications were excluded for not meeting the inclusion criteria as articles or reviews, while 191 were considered irrelevant due to the broad scope of the search terms. Ultimately, 277 articles were included in the analysis, as depicted in *Figure 1*.

Trends in publications and RRI over time are illustrated in *Figure 2*. The number of publications showed a notable upward trend, increasing from 7 in the period between 2006 and 2012 to 88 in 2022. By the time of data collection

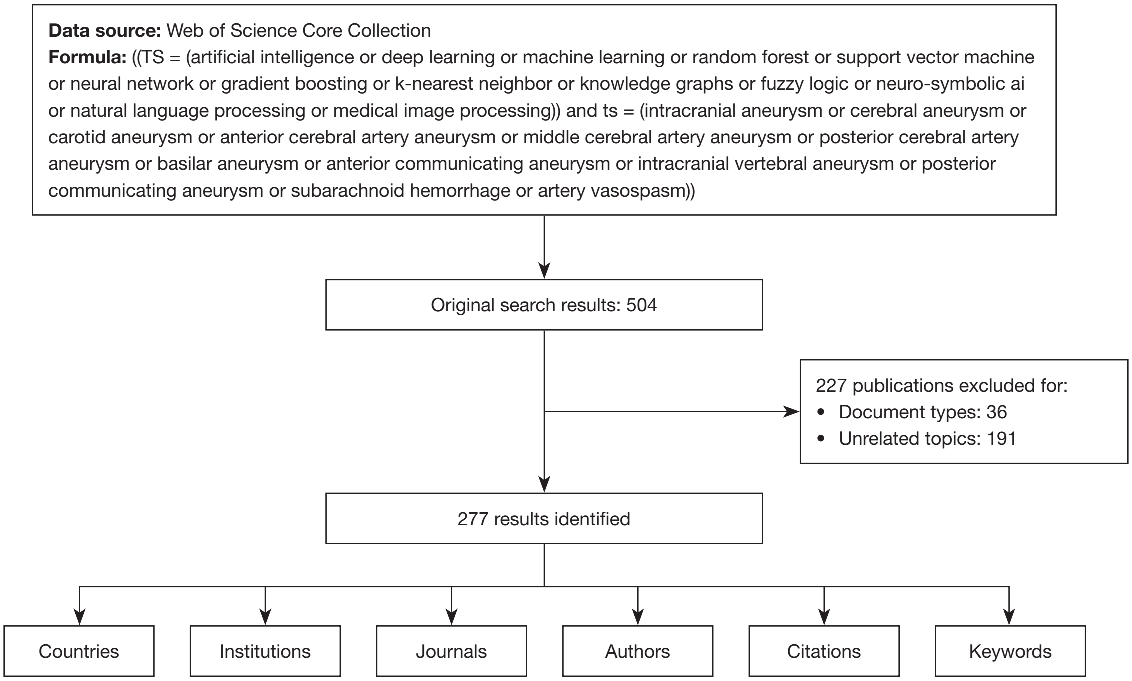


Figure 1 Flow chart of screening procedure and bibliometric analysis. TS is the symbol of searching the topics of papers (including title, abstract, and indexing).

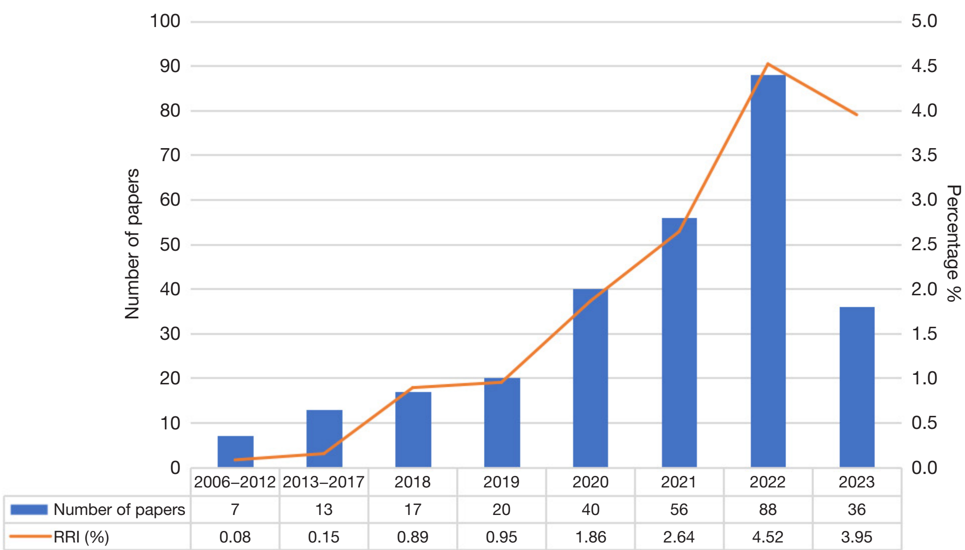


Figure 2 The number of papers and the RRI per year. RRI, relative research interest.

in 2023 (before July 20th), there were 36 publications. Similarly, the RRI witnessed a substantial rise from 0.0008 in the period between 2006 and 2012 to 0.0452 in 2022. The contributions to the IAMWAIT theme emanated from 39 countries, 600 institutions, 1,764 authors, 133 journals, and resulted in 3,197 citations.

Countries

Table 1 displays the distribution of papers, total citation

Table 1 The top 10 countries in IAMWAIT

Country	Papers	Total citations	Average paper citations (%)	GDP (trillion dollars)*
China	118	825	7.0	170.9
USA	82	1,618	19.7	305.9
Germany	25	264	10.6	63.9
Japan	21	329	15.7	86.2
England	15	94	6.3	47.3
South Korea	13	181	13.9	23.2
Australia	12	113	9.4	22.1
Switzerland	10	70	7.0	10.4
Canada	7	58	8.3	28.4
France	7	28	4.0	46.4

*, GDP was calculated by summing from 2006 to 2022. IAMWAIT, intracranial aneurysm management with artificial intelligence technology; GDP, gross domestic product.

counts, average paper citations, and GDP by country. Presently, China has emerged as the most prolific country, accounting for 118 papers (42.6% of the total) and garnering 825 citations. The United States boasts the highest total citation count, amassing 1,618 citations, and also holds the highest average paper citations, with an average of 19.7 citations per paper. China, the United States, and Australia were the most frequent collaborators in research efforts. International collaborations were notable for both the United States and China, with nine overseas partnerships each (*Figure 3A,3B*). Notably, both the total number of papers (r=0.8207, P=0.0036) and the total citation count (r=0.9854, P<0.0001) showed positive and significant correlations with the GDP of countries (*Figure 3C,3D*).

Institutions

Table 2 provides a comprehensive ranking of the top 10 institutions based on their productivity in the IAMWAIT field. Of these institutions, 5 are located in China, 4 in the United States, and 1 in Australia. Capital Medical University emerged as the most productive institution, leading the chart with the highest number of published papers (China, n=17). Following closely were the Chinese Academy of Sciences (China, n=11) and Fudan University (China, n=11). Notably, the University of California System (USA) secured the maximum number of citations, with its publications receiving citations 229 times, and an H-index of 6. It was followed by the State University of New York Suny System (USA) with 200 citations and an H-index of 8, and Harvard University (USA) with 184 citations and an H-index of 7.

Journals

Table 3 presents the top 10 journals in the IAMWAIT field based on their publication output. *Frontiers in Neurology* holds the top position, publishing 19 papers, constituting 6.9% of the total output. The *Journal of Interventional Neurosurgery* follows with 14 papers (5.1%), and the *American Journal of Neuroradiology* with 10 papers (3.6%). Among the most cited journals, *Stroke* stands out with 3,185 citations, followed by the *American Journal of Neuroradiology* with 269 citations, and *European Radiology* with 249 citations.

The dual-map overlay provides a visual representation of the characteristics of journals within the IAMWAIT field (12). Analysis of citation publications revealed a concentration of works in the neurological discipline, with additional contributions in the fields of medicine, molecular biology, and immunology. Interestingly, the most frequently cited papers were published in journals specializing in psychology, education, society, health, nursing, medicine, molecular biology, and genetics. The majority of cited journals were affiliated with the imaging and neurosurgery fields, with *Stroke*, *American Journal of Neuroradiology*, *Neurosurgery*, *Journal of Neurosurgery*, *Radiology*, *Lancet*, and *Journal of Biomechanics* having the largest circle size,

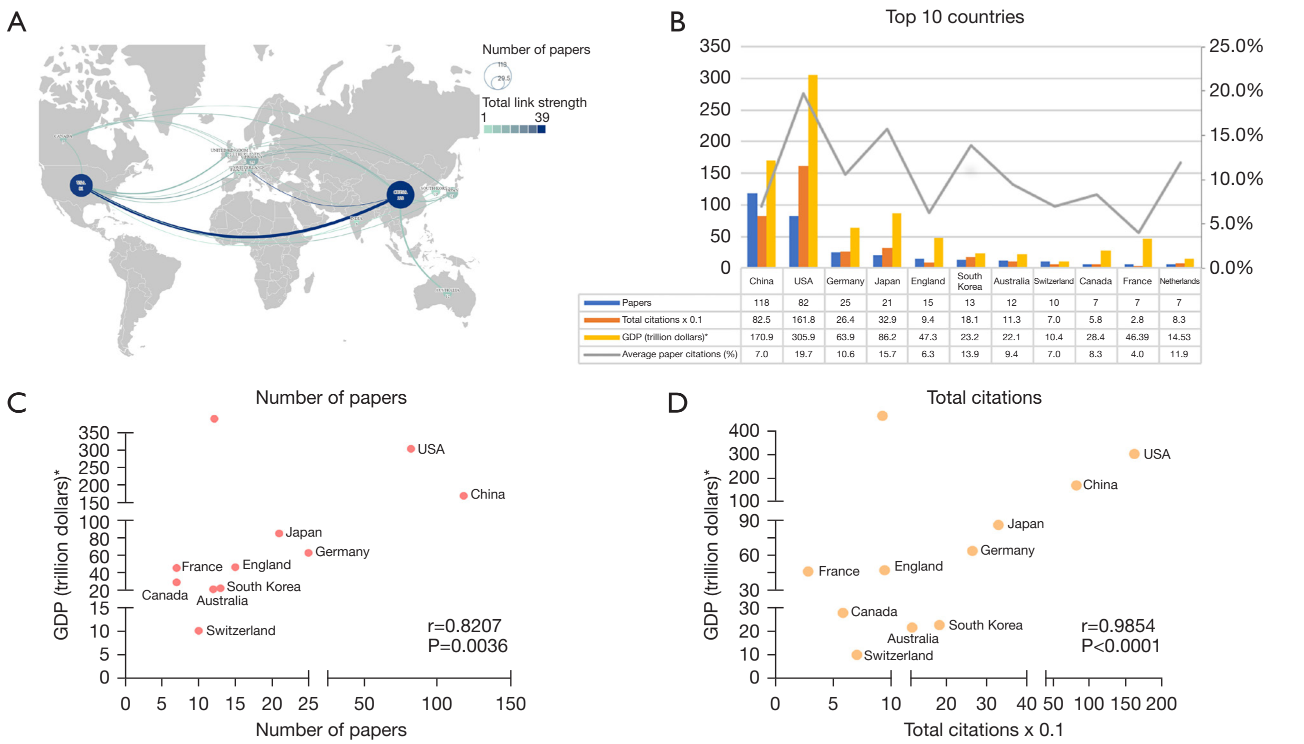


Figure 3 Visualization of the top 10 countries in IAMWAIT. (A) The collaborative map of countries. The size of the pattern indicates the number of published articles. The color of the pattern and link width indicates the cooperation strength. The number of papers, total citations (×0.1), and average citations per article in the top 10 most productive countries; (B) a histogram of the number of papers, total citations (×0.1), average paper citations (%), and GDP; (C) the correlation between GDP and the total number of papers; (D) the correlation between GDP and the number of total citations. *, GDP was calculated by summing from 2006 to 2022. IAMWAIT, intracranial aneurysm management with artificial intelligence technology; GDP, gross domestic product.

Table 2 The top 10 prolific institutions in IAMWAIT

Rank	Institution	Country	Papers	Citations	Average paper citations	H-index
1	Capital Medical University	China	17	123	7.24	5
2	Chinese Academy of Sciences	China	11	42	3.82	4
3	Fudan University	China	11	20	1.82	2
4	State University of New York Suny System	USA	10	200	20.00	8
5	Macquarie University	Australia	9	108	12.00	5
6	Shanghai Jiao Tong University	China	9	78	8.67	3
7	Southern Medical University	China	9	48	5.33	3
8	The University of California System	USA	9	229	25.44	6
9	The University of Texas System	USA	9	55	6.11	5
10	Harvard University	USA	9	184	23.00	7

IAMWAIT, intracranial aneurysm management with artificial intelligence technology.

Table 3 The top 10 prolific journals in IAMWAIT

Rank	Journal	Papers	Citations	IF	Quartile in category	H-index
1	*Front Neurol*	19	68	3.4	Q2	4
2	*J Neurointerv Surg*	14	121	4.8	Q1	5
3	*Am J Neruoradiol*	10	269	3.5	Q2	6
4	*Eur Radiol*	10	249	5.9	Q1	6
5	*Int J Comput Assist Radiol Surg*	10	68	3.0	Q2	4
6	*World Neurosurg*	9	96	2.0	Q4	4
7	*Scientific reports*	5	74	4.6	Q2	3
8	*Stroke*	5	3,185	8.3	Q1	27
9	*Acta Neurochir*	4	31	2.7	Q2	3
10	*Comput Methods Programs Biomed*	4	14	6.1	Q1	2

IF, impact factor; IAMWAIT, intracranial aneurysm management with artificial intelligence technology.

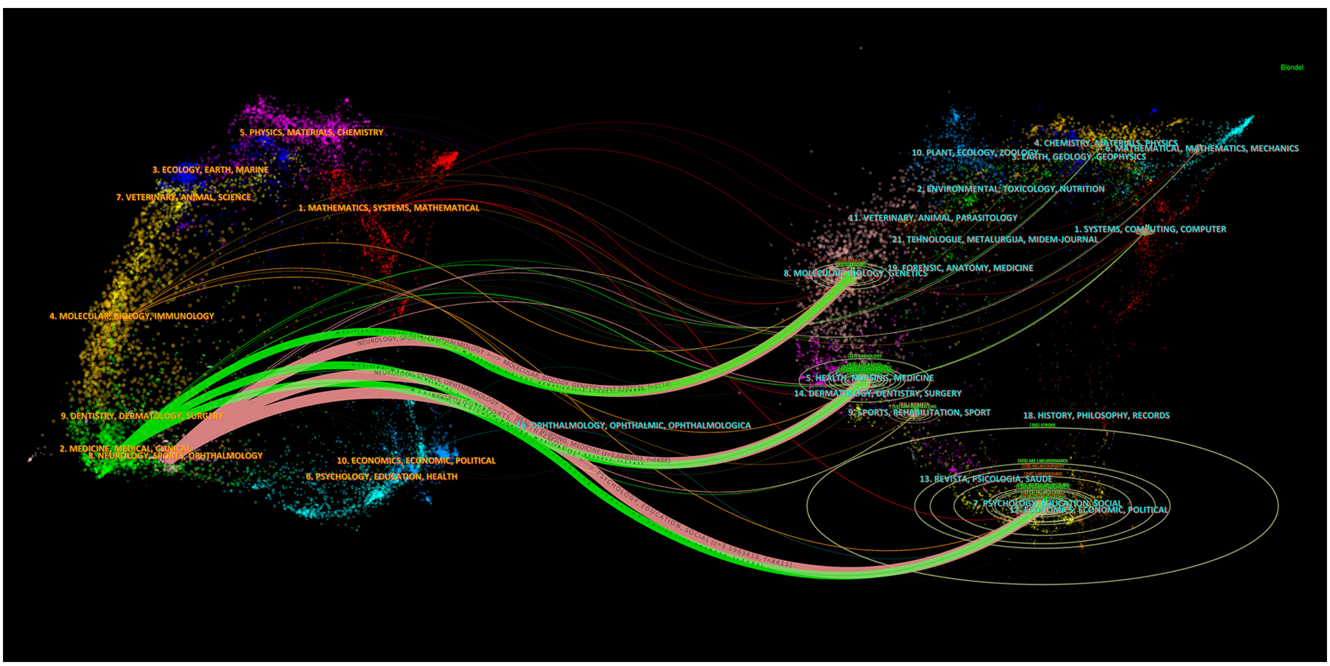


Figure 4 The dual-map overlay of papers citing IAMWAIT. IAMWAIT, intracranial aneurysm management with artificial intelligence technology.

indicative of their high citation frequency (see *Figure 4*).

Authors

Table 4 presents the top 10 authors with the highest publication output and the top 10 co-cited authors, with a significant representation from China. The top 10 co-cited authors were identified based on the number of citations accrued within the IAMWAIT field. Duan Chuan-Zhi (n=9 papers), Ou Chubin (n=7 papers), Zhang Xin (n=7 papers), Yang Yunjun (n=7 papers), and Chen Yongchun (n=7 papers) emerged as the most prolific authors.

Figure 5 provides a visual representation of the collaborative author network in the IAMWAIT field and the

Table 4 Top 10 prolific authors

Rank	Author	Country	Institution	Publications
1	Duan, Chuan-Zhi	China	Southern Medical University	9
2	Ou, Chubin	China	The First People's Hospital of Foshan	7
3	Zhang, Xin	China	Southern Medical University	7
4	Yang, Yunjun	China	Wenzhou Medical University	7
5	Chen, Yongchun	China	National Engineering Laboratory of Coal Mine Ecological Environment Protection	7
6	Lin, Boli	China	Wenzhou Medical University	6
7	Meng, Hui	USA	State University of New York at Buffalo	5
8	Li, Youxiang	China	Capital Medical University	5
9	Snyder Kenneth	USA	State University of New York at Buffalo	5
10	Zhou, Jiafeng	China	East China Normal University	5

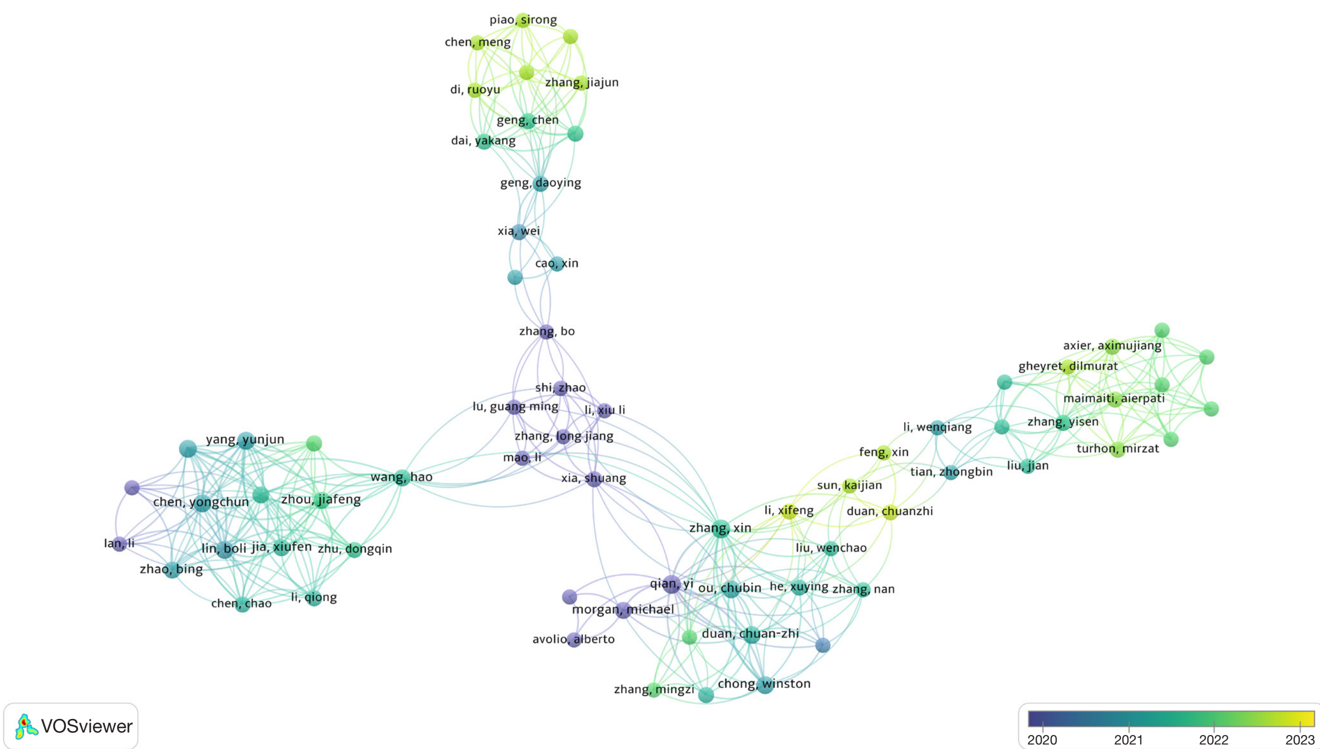


Figure 5 The collaborative network of authors involved in IAMWAIT studies. The color coding represents the average publication year of each author, while the size of each node corresponds to the number of papers authored by that individual. To enhance clarity, only authors with a minimum of 2 papers were included in the network. Out of a total of 1,821 authors, 269 met the publication threshold and were displayed in the graph, depicting the most significant interconnected items within the network. IAMWAIT, intracranial aneurysm management with artificial intelligence technology.

Table 5 The top 10 papers with the highest number of citations

Rank	Cited papers	Publication type	Country	Citations	IF
1	Chilamkurthy, 2018, *Lancet* (13)	Article	India	387	168.9
2	Chang, 2018, *Am J Neruoradiol* (14)	Article	USA	134	3.5
3	Park, 2019, *JAMA Netw Open* (15)	Article	USA	107	13.8
4	Ye, 2019, *Eur Radiol* (16)	Article	China	103	5.9
5	Ueda, 2019, *Radiology* (17)	Article	Japan	96	19.7
6	Nakao, 2018, *J Magn Reson Imaging* (18)	Article	Japan	96	4.4
7	Ker, 2019, *Sensors (Basel)* (19)	Article	Singapore	91	3.9
8	Sichtermann, 2019, *Am J Neruoradiol* (20)	Article	Germany	69	3.5
9	Castro, 2017, *Neurology* (21)	Article	USA	58	9.9
10	Liu, 2019, *Stroke* (22)	Article	China	54	8.3

IF, impact factor.

co-cited author network. Notably, Zhang Longjiang, Morgan Michael, and were active during the early stages of the field (i.e., 2020), while Duan Chuan-Zhi, Sun Kaijiang, Feng Xin, and were active during the later stages (i.e., 2022 to 2023).

Cited papers and co-cited references

Table 5 presents a comprehensive list of the top 10 most highly cited papers from a total of 277 papers in the IAMWAIT field. These papers were authored by researchers from the USA (n=3), China (n=2), Japan (n=2), Germany (n=1), India (n=1), and Singapore (n=1). Of note, Chilamkurthy *et al.* (13) published the paper with the highest number of citations (91 times) in the *Lancet* in 2018, entitled "Deep learning algorithms for detection of critical findings in head CT scans: a retrospective study". Their study focused on the development of a deep learning model for aiding in the diagnosis of aneurysms on head computed tomography (CT) scans.

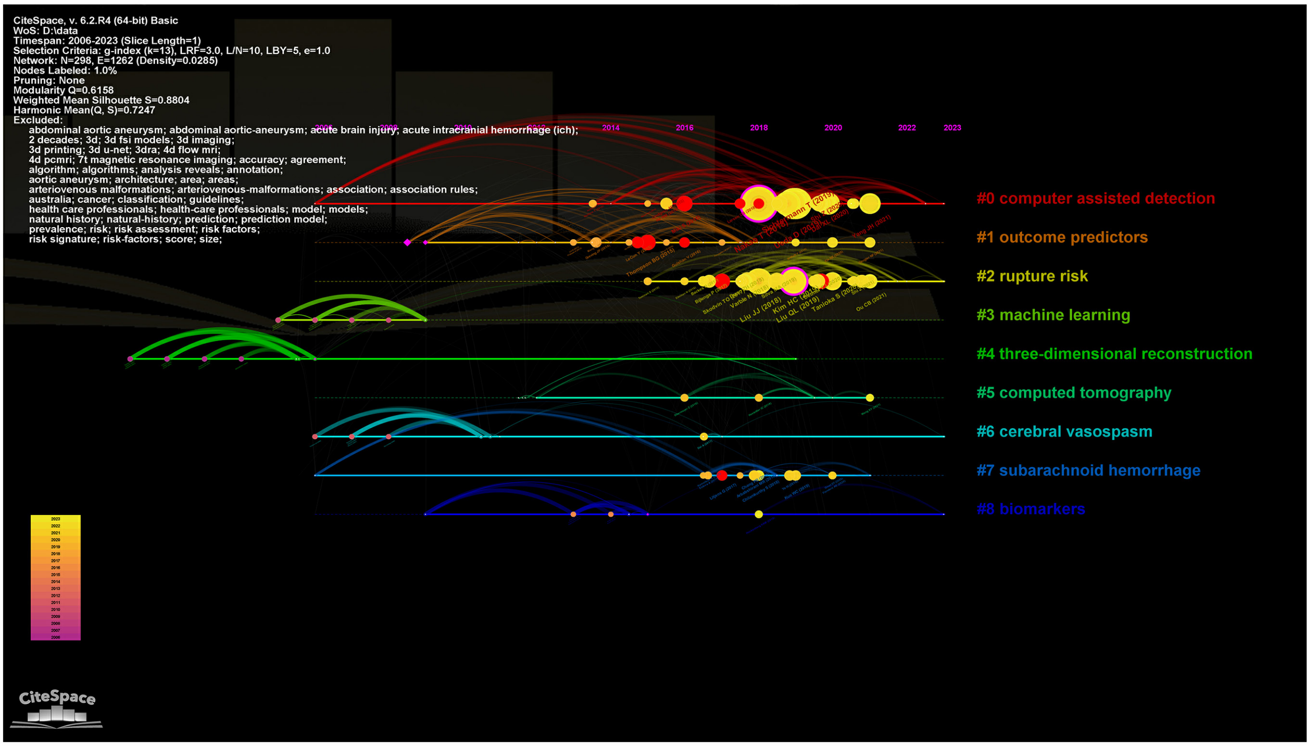
The timeline map of the reference clusters identified 9 distinct clusters with modularity Q score and silhouette score values of 0.6158 (>0.3) and 0.8804 (>0.7), respectively. References play a pivotal role in shaping research directions, and cluster analysis of references can effectively highlight the prominent areas of research in published papers. In this study, the clusters pointed to 6 main categories within IAMWAIT, namely, "computer-assisted detection", "outcome predictors", "rupture risk", "three-dimensional reconstruction", "cerebral vasospasm", and "biomarkers" (*Figure 6A*). "Computer-assisted detection" encompassed references focusing on the detection and diagnosis of IAs through AI technology. "Outcome predictors" involved references related to outcome prediction of IAs after treatment, encompassing growth prediction, vasospasm prediction, complications prediction, and others. "Rupture risk" references were centered on the prediction of rupture for unruptured IAs. "Three-dimensional reconstruction" pertained to IA segment and reconstruction references. "Cerebral vasospasm" included keywords related to vasospasm prediction after treatment. Finally, "biomarkers" referred to references in the domain of metabolic fingerprints, gene expression, inflammation, immune microenvironment, and related areas. Notably, references in the "three-dimensional reconstruction" category were the earliest, dating back to 1998. The majority of references were published between 2016 and 2021, particularly in the areas of "computer-assisted detection" and "rupture risk".

Citations for most of the references occurred between 2013 and 2023 (*Figure 6B*). Early references with the strongest citation bursts between 2013 and 2014 were Zuva *et al.* (23), Bederson *et al.* (24), and Lesage *et al.* (25), which focused on IA segment and rupture. Conversely, the reference with the highest strength pertained to computer-assisted detection of IAs, published by Nakao *et al.* (18) in the *Journal of Magnetic Resonance Imaging*, and experienced a notable surge in citations from 2019 through 2021.

Keywords

The Sankey diagram in *Figure 7A* illustrates the evolution

A



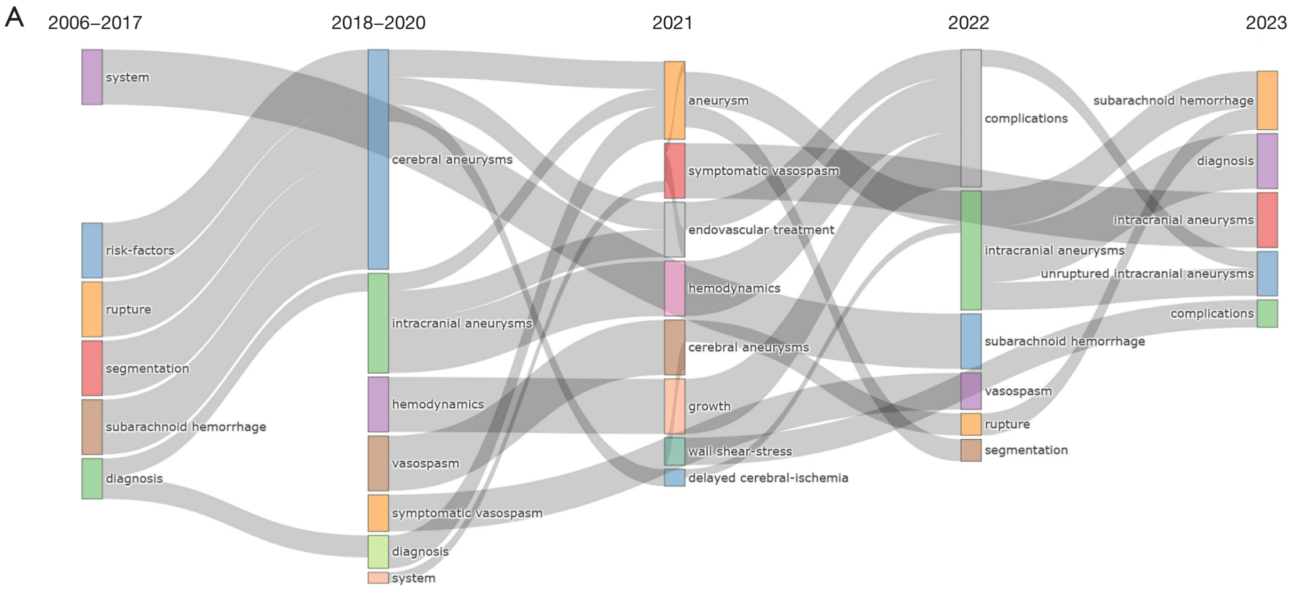
B

Top 25 references with the strongest citation bursts

References	Year	Strength	Begin	End	2006–2023
Zuva T, 2011, CANADIAN J IMAGE PRO, V2, P20	2011	1.21	2013	2014	
Bederson JB, 2009, STROKE, V40, P994, DOI 10.1161/STROKEAHA.108.191395, DOI	2009	1.21	2013	2014	
Lesage D. 2009, MED IMAGE ANAL, V13, P819, DO1 10.1016/j.media.2009.07.011, DOI	2009	1.21	2013	2014	
Greving JP, 2014, LANCET NEUROL, V13, P59, DOI 10.1016/S1474-4422(13)70263-1, DO1	2014	2.74	2018	2018	
Meng H, 2014, AM J NEURORADIOL, V35, P1254, DOI 10.3174/ajnr.A3558, DOI	2014	2.05	2018	2018	
Gulshan V, 2016, JAMA-J AM MED ASSOC, V316, P2402, DOI 10.1001/jama.2016.17216, DOI	2016	1.36	2018	2018	
Nakao T, 2018, J MAGN RESON IMAGING, V47, P948, DOI 10.1002/jmri.25842, DOI	2018	9.96	2019	2021	
Krizhevsky Alex, 2017, COMMUNICATIONS OF THE ACM, V60, P84 DOI 10.1145/3065386, DOI	2017	2.01	2019	2019	
Kamnitsas K, 2017, MED IMAGE ANAL, V36, P61, DOI 10.1016/j.media.2016.10.004, DOI	2017	2.01	2019	2019	
Esteva A, 2017, NATURE, V542, P115, DOI 10.1038/nature21056, DOI	2017	2.01	2019	2019	
Sichtermann T, 2019, AM J NEURORADIOL, V40, P25, DOI 10.3174/ajnr.A5911, DOI	2019	7.34	2020	2023	
Ueda D, 2019, RADIOLOGY, V290, P187, DOI 10.1148/radio1.2018180901, DOI	2019	6.82	2020	2021	
Park A, 2019, JAMA NETW OPEN, V2, P0, DOI 10.1001/jamanetworkopen.2019.5600, DOI	2019	6.37	2020	2023	
Thompson BG, 2015, STROKE, V46, P2368, DOI 10.1161/STR.0000000000000070, DOI	2015	3.72	2020	2020	
He KM, 2016, PROC CVPR IEEE, V0, PP770, DOI 10.1109/CVPR.2016.90, DOT	2016	3.81	2021	2021	
Arbabshirani MR, 2018, NPJ DIGIT MED, V1, P0, DOI 10.1038/s41746-017-0015-z, DOI	2018	3.16	2021	2021	
Liu QL, 2019, STROKE, V50, P2314, DOI 10.1161/STROKEAHA.119.025777, DOI	2019	7.27	2022	2023	
Shi Z, 2020, NAT COMMUN, V11, P0, DOI 10.1038/s41467-020-19527-w, DOI	2020	5.89	2022	2023	
Stember JN, 2019, J DIGIT IMAGING, V32, P808, DOI 10.1007/s10278-018-0162-z, DOI	2019	5.89	2022	2023	
Dai XL, 2020, INT J COMPUT ASS RAD, V15, P715, DOI 10.1007/s11548-020-02121-2, DOI	2020	5.71	2022	2023	
Yang JH, 2021, RADIOLOGY, V298, P155, DOI 10.1148/radiol.2020192154, DOI	2021	4.87	2022	2023	
Silva MA, 2019, WORLD NEUROSURG, V131, PE46, DOI 10.1016/j.wncu.2019.06.231, DOI	2019	4.45	2022	2023	
Macdonald RL, 2017, LANCET, V389, P655, DOI 10.1016/S0140-6736(16)30668-7, DOI	2017	4.45	2022	2023	
Liu JJ, 2018, EUR RADIOL, V28, P3268, DOI 10.1007/s00330-017-5300-3, DOI	2018	4.45	2022	2023	
Kim HC, 2019, J CLIN MED, V8, P0, DOI 10.3390/jcm8050683, DOI	2019	4.21	2022	2023	

Figure 6 Visualization of co-cited reference analysis. (A) The timeline map of the clusters; (B) the strongest citation bursts of the top 25 co-cited references. On the blue line, the red segment indicates the duration of the references being followed.

A



B

Top 25 Keywords with the strongest citation bursts

Keywords	Year	Strength	Begin	End	2006–2023
Fuzzy logic	2006	1.33	2006	2010	
Segmentation	2006	0.73	2006	2012	
System	2009	1.35	2009	2010	
Logistic regression	2009	1.23	2009	2015	
Surgery	2010	1.62	2010	2018	
Brain	2012	1.53	2012	2018	
Images	2012	1.38	2012	2020	
Dysfunction	2013	0.73	2013	2020	
Patient	2014	1.52	2014	2020	
Decision support system	2014	1.24	2014	2017	
Dynamics	2014	1.03	2014	2019	
Digital subtraction angiography (dsa)	2017	1.23	2017	2018	
Artificial neural network	2017	0.66	2017	2021	
Critical care	2018	1.13	2018	2019	
Continuous eeg	2018	0.86	2018	2020	
Blood	2018	0.74	2018	2019	
Angiography	2006	2.93	2019	2020	
Subarachnoid hemorrhage	2014	2.08	2019	2020	
Computed tomography	2012	1.52	2019	2020	
CT	2019	1.13	2019	2021	
Digital subtraction angiography	2019	1.04	2019	2021	
Computer-aided detection	2019	0.97	2019	2020	
Circle	2020	1.13	2020	2021	
Endovascular treatment	2020	0.98	2020	2023	
Outcome prediction	2021	0.94	2021	2023	

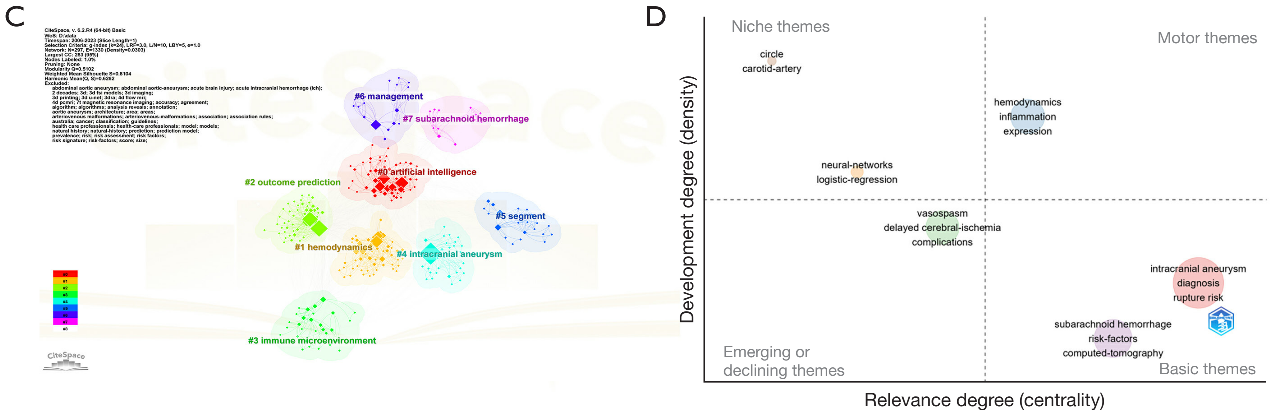


Figure 7 Visualization of keyword analysis. (A) The Sankey diagram portrays the evolution of keywords across distinct time periods, including 2006–2017, 2018–2020, 2021, 2022, and 2023. (B) The top 25 keywords with the most robust citation bursts. The blue line represents the timeline, while the red segment highlights the duration during which a particular keyword experiences a concentration of citations. (C) The keywords network with cluster visualization in IAMWAIT. Synonymous keywords were merged and unrelated keywords were excluded. (D) The thematic evolution analysis of IAMWAIT. IAMWAIT, intracranial aneurysm management with artificial intelligence technology.

of keywords over different periods of article publication, divided into five segments: 2006–2017, 2018–2020, 2021, 2022, and 2023. During the period from 2006 to 2017, keywords such as "rupture", "segmentation", "subarachnoid hemorrhage", and "diagnosis" were prominent. From 2018 to 2020, important keywords that emerged included "hemodynamics", "vasospasm", and "diagnosis", among others. In 2021, novel keywords like "symptomatic vasospasm", "endovascular treatment", "hemodynamics", and "growth" gained significance. In 2022, the emergence of "complication", "subarachnoid hemorrhage", "vasospasm", "rupture", and "segmentation" as key keywords was observed. By 2023, "subarachnoid hemorrhage", "diagnosis", and "complication" were the major keywords.

Figure 7B displays the top 25 keywords with the most citations. Notably, "fuzzy logic" and "segment" were among the earliest burst words, dating back to 2006 to 2012. Keywords like "disfunction", "decision support system", "dynamics", and "digital subtraction angiography" emerged during the middle period from 2013 to 2020. More recent burst words from 2019 to 2023 included "subarachnoid hemorrhage", "computer-aided detection", and "outcome prediction", among others.

To provide clarity, the keywords were clustered into eight groups, as shown in *Figure 7C*, with a modularity Q score and silhouette score of 0.5102 (>0.3) and 0.8104 (>0.7), respectively. The most critical cluster was centered around "artificial intelligence", followed by clusters focusing on "hemodynamics", "outcome prediction", "immune microenvironment", "segment", "subarachnoid hemorrhage", and others. Merged proximal words were excluded for clarity (Table S1), and irrelevant keywords were also excluded (Table S2).

Figure 7D, the thematic map, visually represents the importance and development of themes in IAMWAIT, guiding scientific research themes. Keywords such as "hemodynamics", "inflammation", and "expression" were identified as important and well-developed themes. Themes like "diagnosis" and "rupture risk" were important but not as well-developed, while emerging themes in the field included "vasospasm", "delay cerebral-ischemia", and "complications".

Discussion

This study presents a comprehensive bibliometric analysis of the rapidly developing field of IAMWAIT, encompassing 277 papers published until July 20, 2023. Over the years, IAMWAIT has witnessed significant growth, with the number of publications rising from 7 in the period between 2006 and 2012 to 88 in 2022, resulting in a substantial increase in the RRI from 0.11% to 3.59%, indicating a growing interest in this field. China was very active and most involved whereas the United States had the strongest impact in this field. The main research themes, of interest in this field are hemodynamics, rupture risk assessment/prediction, outcome prediction (growth prediction, ischemic or hemorrhage event prediction, vasospasm prediction, etc.), computer-assisted diagnosis, basic research of IA (metabolic fingerprints, gene-expression, inflammation, immune microenvironment, etc.), and IA segment. Among these themes, computer-assisted diagnosis has lasted the longest, and outcome prediction was the latest theme. The most prolific journal in this field is *Frontiers in Neurology*, while *Stroke* has the largest number of citations.

Countries

Regarding the geographic distribution of publications and impact in the field of IAMWAIT, China has emerged as a leading contributor, producing the highest number of publications (n=118), with representation from five top prolific institutions and collaborations with nine different countries. Notably, China's close collaborations with the United States and Australia indicate its significant contributions to the development of AI technology in the medical field, in line with the findings of a previous study (26).

The United States holds the largest world influence in the IAMWAIT field, evident from its highest number of total citations (n=1,618), presence in the top 3 institutions for citations/H index, collaborations with nine countries, and three of the top 10 cited papers, ranked second, third, and ninth, respectively. These findings underscore the strong scientific strength of the United States and its potential for knowledge exchange and collaboration, which aligns with similar observations in bibliometric reports of other fields, such as the treatment of diffuse intrinsic pontine glioma (27) and urological surgery (28).

Furthermore, among the top 10 papers with the highest number of citations, notable contributions come from India, Japan, Singapore, and Germany. Australia, represented by a prolific institution with a high number of citations, also significantly contributed to the development of IAMWIAT. These countries' presence in the top-cited papers highlights their significant impact in the field and their active participation in driving advancements in AI technology for IA management. The bibliometric analysis reveals a strong positive correlation between the number of papers and GDP, and the number of citations and GDP, suggesting that the economic level of the countries has a significant impact on the application of AI technology. A bibliometric analysis by Wang *et al.* also found a similar correlation between GDP and moyamoya disease management (29).

Journals

Regarding journal publications, *Frontiers in Neurology* emerged as the most prolific journal, having published a total of 15 papers (n=19) in the field of IAMWAIT. On the other hand, *Stroke* demonstrated the highest number of citations, accumulating an impressive total of 3,185 citations. Furthermore, *Stroke* exhibited the highest H-index and impact factor (IF), indicative of its substantial influence and reputation within the field. The outcomes of this journal analysis offer valuable insights to researchers, guiding them in selecting appropriate journals for disseminating their IAMWAIT-related work. Furthermore, it is pertinent to highlight that among the most highly cited journals in IAMWAIT, several publications dedicated to computing, mathematics, and biomedicine actively contributed to supporting research endeavors related to IAMWAIT. This noteworthy observation underscores the interdisciplinary nature of the field and the active involvement of diverse journals in advancing knowledge and innovations in this area.

Sub-fields of IAMWAIT

Sub-fields of IAMWAIT can be identified through cluster analysis of co-cited references and keywords, revealing the prominent areas of research within this domain. Special attention has been given to highlighting the emerging trends and potential future directions for research within each sub-field. By doing so, we aim to offer a comprehensive outlook for researchers and practitioners, facilitating their endeavors to explore new avenues of investigation and innovation. The primary fields of AI technology applied in IAMWAIT encompass rupture risk assessment/prediction, computer-assisted diagnosis, outcome prediction, hemodynamics, and laboratory research of IAs.

The accurate differentiation of the rupture risk of IAs holds paramount importance due to its potential impact on treatment optimization and improved patient outcomes (5). Over time, the parameters used in rupture risk prediction studies have expanded. Initially, clinical characteristics, aneurysm size, and IA location were utilized to develop AI models (30). Subsequently, studies incorporated morphological parameters such as aspect ratio (AR) and size ratio (SR). For instance, Zhu *et al.* (6) devised an AI model based on clinical and morphological features to predict rupture risk, surpassing the performance of traditional logistic regression models and the PHASES score. More recently, parameters of hemodynamics and radiomics have been integrated into AI-powered rupture risk prediction models (22,31). In the future, the inclusion of newly proposed parameters is anticipated to further enhance the AI models, providing novel perspectives and improving predictive accuracy. For example, Yang *et al.* (32) introduced a novel morphological index, the mass moment of inertia, which quantifies the shape irregularity of unruptured IAs and addresses the limitations of previous subjective determinations.

In the context of computer-assisted diagnosis, the application of AI algorithms holds significant promise in reducing radiologists' reading time and improving diagnostic performance within clinical settings (33). Particularly, AI has shown remarkable potential in automating the segmentation of intracranial arteries and detecting IAs. This theme has garnered substantial attention in the field of IAMWAIT, with half of the top 10 most cited papers focusing on this subject (13,15,17-20). Leveraging extensive medical imaging data, AI algorithms have demonstrated the capacity to enhance the accuracy and efficiency of aneurysm detection and segmentation, providing valuable diagnostic support to medical professionals. Notably, convolutional neural networks (CNNs), a type of AI algorithm, have emerged as a revolutionary tool in computer-assisted diagnosis, exhibiting the potential to expedite processes and improve result consistency (34). However, some limitations have been reported, particularly in simulating blood vessels (35). As a consequence, there is an ongoing need for the creation or updating of novel AI algorithms to address these specific shortcomings. Studies such as those conducted by Lee *et al.* (36) and Jin *et al.* (37) have ventured into developing new deep-learning algorithms to overcome these challenges. Moreover, there has been a shift in the focus of research, with an increasing emphasis on time-of-flight MR angiography (TOF-MRA) as a primary non-invasive screening method for IAs, in contrast to the previous concentration on digital subtraction angiography (DSA) (38). Additionally, some studies have extended the application of AI to encompass both diagnosis and rupture prediction, exemplified by the work of Hentschke *et al.* (39). Furthermore, recent trends in IAMWAIT research indicate greater availability of large annotated datasets, a heightened emphasis on data safety and ethical considerations, and a growing interest in integrating aneurysm detection and segmentation algorithms into clinical workflow systems.

Outcome prediction represents a novel and significant theme in the field of IAMWAIT, playing a crucial role in clinical decision-making. Within outcome prediction, the sub-fields of complication (ischemic or hemorrhage event) prediction, vasospasm prediction after treatment, and growth prediction of unruptured IAs have emerged as areas of particular interest in this study. Notable contributions include Tanioka *et al.*'s creation of an AI model for predicting delayed cerebral ischemia (40), Kim *et al.*'s development of an AI-explainable predictive model for vasospasm prediction (41), and Bizjak *et al.*'s model to predict the growth of untreated IAs based on baseline aneurysm morphology (42). Additionally, some potential sub-fields, such as recurrence prediction for IAs after treatment (43) and effectiveness prediction after endovascular treatment (44), remain underexplored and warrant further investigation in the future.

Hemodynamic simulation, facilitated by AI models of blood flow, proves to be a valuable tool in the management of IAs. Integrating hemodynamic parameters into rupture predictive models, as demonstrated by Yang *et al.*, has shown promise in improving the predictive accuracy of these models (45). Hemodynamic analysis powered by AI has been applied to outcome prediction, rupture prediction, and growth prediction (46-48). Further explorations in this field hold potential, including the use of 4D phase-contrast magnetic resonance imaging (4D pcMRI) as an imaging acquisition method (49) and guiding stent placement during procedures (50). Notably, IA segmentation methods are a necessary step in creating computational fluid dynamics (CFD) models for hemodynamic analysis. Presently, standard procedures for IA segmentation rely on manual segmentation, which may introduce errors and time constraints. The development of AI-powered automated segmentation holds promise as a future direction (51).

Laboratory research of IA, encompassing investigations into metabolic fingerprints, gene expression, inflammation, immune microenvironment, and related aspects, holds promise in providing valuable insights into the inflammatory response associated with IA. Such research can play a pivotal role in advancing diagnosis, outcome prediction, and rupture risk assessment, among other crucial aspects (52-54). By leveraging AI algorithms, laboratory research endeavors can experience significant time savings and increased efficiency, thus accelerating the pace of discoveries in this domain. However, it is pertinent to note that the incorporation of gene expression, metabolic markers, and similar factors into routine clinical examinations has faced criticism, possibly limiting their current instructiveness for IA management in clinical settings. Thus, the endeavor to bridge the gap between research findings and real-world clinical applications becomes a vital direction for future investigations.

This study boasts several noteworthy strengths. Firstly, it is the first bibliometric analysis conducted in the field of IAMWAIT, which has recently gained significant attention and shows great potential. Secondly, to achieve comprehensive and high-quality visualization results, we utilized multiple bibliometric analysis software. Despite these strengths, the study does present certain limitations that warrant acknowledgment. Foremost among them is the utilization of the WoSCC dataset, which, while being the most comprehensive source compatible with VOSviewer and CiteSpace, may not entirely represent the entirety of IAMWAIT. As a result, some literature within the field might not have been fully captured in this analysis. Moreover, the prevalence of certain keywords or co-cited references may have led to potential overrepresentation, potentially resulting in limited coverage of all areas within the diverse domain of IAMWAIT.

Conclusions

The field of IAMWAIT has undergone rapid and significant development in recent years, with AI emerging as a powerful tool capable of addressing various critical aspects, including rupture risk assessment/prediction, computer-assisted diagnosis, outcome prediction, hemodynamics, and laboratory research related to IAs. Looking ahead, there is a pressing need to further explore the potential applications of AI algorithms in additional sub-fields within IAMWAIT, fostering a more comprehensive and versatile approach. Moreover, it is imperative to optimize AI algorithms to align them better with real-world clinical settings, facilitating their seamless integration and practical utility in the management of IA patients. By actively pursuing these research directions, the field can unlock the full potential of AI in IAMWAIT, ushering in a new era of enhanced patient care and clinical outcomes.

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Footnote

Conflicts of Interest: All authors have completed the ICMJE uniform disclosure form (available at https://qims.amegroups.com/article/view/10.21037/qims-23-793/coif). The authors have no conflicts of interest to declare.

Ethical Statement: The authors are accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

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Supplementary

Table S1 Thesaurus

Label	Replace by
cerebral aneurysm	intracranial aneurysm
cerebral aneurysm (ca)	intracranial aneurysm
intracranial aneurysms	intracranial aneurysm
cerebral aneurysms	intracranial aneurysm
aneurysm	intracranial aneurysm
aneurysms	intracranial aneurysm
artery aneurysm	intracranial aneurysm
saccular intracranial aneurysm	intracranial aneurysm
aneurysm rupture risk prediction	rupture risk
aneurysm rupture risk	rupture risk
aneurysm rupture	rupture risk
rupture	rupture risk
aneurymal subarachnoid hemorrhage	subarachnoid hemorrhage
aneurysmal subarachnoid hemorrhage (asah)	subarachnoid hemorrhage
hemorrhagic stroke	subarachnoid hemorrhage
stroke	subarachnoid hemorrhage
stroke-council	subarachnoid hemorrhage
diagnosis	assisted detection
diagnosis	aided detection
diagnosis	aided diagnosis
diagnosis	aneurysm detection
diagnosis	automatic detection
diagnosis	computer aided detection
diagnosis	computer assisted detection
diagnosis	computer-aided detection (cade) system
diagnosis	computer-aided diagnosis
diagnosis	computer-assisted detection
diagnosis	computer-assisted diagnosis
aneurysm growth	aneurysm development analysis
segment	aneurysm segmentation
aneurysm wall	aneurysm wall enhancement
aneurysm wall characterization	aneurysm wall enhancement
arterial-wall	aneurysm wall enhancement
assisted coiling	decision support system
automatic optimization	decision support system
clinical decision making	decision support system
brain hemorrhage	subarachnoid hemorrhage
transcranial doppler ultrasonography	transcranial doppler
transcranial doppler ultrasound	transcranial doppler
unruptured cerebral aneurysms	unruptured intracranial aneurysm
unruptured intracranial aneurysms	unruptured intracranial aneurysm
vasospasm detection	vasospasm
cerebral vasospasm	vasospasm
symptomatic vasospasm	vasospasm

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Table S2 Deleted words

Label
Abdominal aortic aneurysm
Abdominal aortic-aneurysm
Acute brain injury
Acute intracranial hemorrhage (ich)
2 decades
3d
3d fsi models
3d imaging
3d printing
3d u-net
3dra
4d flow mri
4d pcmri
7t magnetic resonance imaging
Accuracy
Agreement
Algorithm
Algorithms
Analysis reveals
Annotation
Aortic aneurysm
Architecture
Area
Areas
Arteriovenous malformations
Arteriovenous-malformations
Association
Association rules
Australia
Cancer
Classification
Guidelines
Health care professionals
Health-care professionals
Model
Models
Natural history
Natural-history
Prediction
Prediction model
Prevalence
Risk
Risk assessment
Risk factors
Risk signature
Risk-factors
Score
Size

 https://dx.doi.org/10.21037/qims-23-793