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Brain tumors. A bibliometric analysis of forty years by science mapping

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ABSTRACT

Objectives: Science mapping is a systematic approach to analyzing the intricate network of relationships in the scientific literature. Science mapping methodology investigates the networks of relationships among scientific articles, authors, journals, keywords, and research topics. This study aims to comprehend the literature in the field of brain tumors.

Methods: Our study covers the period 1980-2022. Our study uses the Web of Science database for literature reviews and bibliometric analyses. The obtained data were filtered and classified. The 10,777 articles were analyzed in five sections. Some of sections are: structural analysis of the articles, analysis of countries, keyword analysis, thematic analysis, and the collaboration analysis.

Results: The articles have been published in 1761 journals. The average citation per article is 38.22. The highest h and g-index values belong to Cancer Research. For thematic analysis, the period from 1980 to 2022 has been analyzed. During 2021-2022, 'Deep Learning' and 'Brain Tumors' formed the motor themes. The authors' collaboration network is analyzed. Kun LE is the author with the most collaborations.

Conclusions: Upon examining thematic maps from all periods, it is assessed that the likely topics and scopes of future research on brain tumors will be biomarkers, personalized treatments, artificial intelligence, immunotherapy, and pediatric brain tumors.

Keywords: Brain tumors, science mapping, thematic analysis, literature, web of science

Brain tumors, also called intracranial neoplasms, are a heterogeneous group of abnormal growths that develop within the brain or surrounding tissues. These tumors may be classified based on their tissue of origin, histological characteristics, and their potential for malignancy. Primary brain tumors originate within the brain itself and can be further categorized into gliomas, meningiomas, and other less common types [1].

Clinical manifestations are variable. Manifestations depend on the tumor's size, location, and growth rate. Common symptoms include headaches, seizures, cognitive impairment, motor deficits, and visual disturbances. Diagnostic modalities encompass neuroimaging techniques, such as magnetic resonance imaging (MRI) and computed tomography (CT) scans, and histopathological examination of biopsy specimens for accurate tumor classification. The management of brain tumors necessitates a multidisciplinary approach. Treatment options include surgical resec-

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tion, radiation therapy, chemotherapy, immunotherapy, and targeted therapies. The prognosis for individuals with brain tumors varies widely, depending on factors such as tumor type, stage, and genetic characteristics [2, 3].

In the United States, there were an estimated 25,000 new cases of primary malignant brain tumors in 2020. In 2020, it was estimated that nearly 18,000 people in the United States died from brain and other nervous system cancers [4].

Science mapping is a systematic approach to analyzing the intricate network of relationships in the scientific literature through quantitative methods and visualization techniques. It serves as a methodology employed to analyze scientific knowledge dynamics visually. This methodology investigates the networks of relationships among scientific articles, authors, journals, keywords, and research topics. Science mapping enables researchers, policymakers, and institutions to discern trends and make informed decisions. Science mapping relies on various data sources that provide access to comprehensive records. Prominent among these sources are academic databases such as Web of Science, PubMed, Scopus, and Google Scholar [5].

This study aims to comprehend the literature in the field of brain tumors, identify the main research topics, and visualize connections that could lead to potential collaborations and new discoveries. These efforts involve analyzing scientific publications on brain tumors to demonstrate how research topics and subfields have evolved. The collaboration among research groups will be utilized to understand the general trends and emphases in the field by identifying significant scientific journals and frequently used terms.

METHODS

Our study's data collection and analysis process is illustrated in Fig. 1. Our study uses the Web of Science (WoS) database for literature reviews and bibliometric analyses. The data scan was conducted on November 15, 2023. The obtained data were filtered and classified. Articles titled "Brain Tumors" and "Brain Tumor" were scanned in the WoS database. The "Research Article" and "Review Article" article types were selected. The language was set to "English," and the WoS index chosen was "SCI, SCI-Expanded, and SSCI" Articles from 2023 were excluded from the scope, as new articles are still being entered into the database. As a result, 10,777 articles were included in the analysis.

The 10,777 articles were analyzed in five sections. The first section involved the structural analysis of the articles. The second section included the analysis of countries, authors, journals, and articles, the third section dealt with keyword analysis, the fourth section comprised thematic analysis, and the fifth included collaboration analysis. The analysis merged the keyword "Brain Tumor" under "Brain Tumors."

Structure Analysis

In this section, analyses have been conducted on articles, journals, the annual increase in the number of articles, total number of authors, authors of single-authored documents, international co-authorship, the average number of co-authors per document, keywords, references, the average age of documents, and the average citations per document.

Countries, Authors, Sources, Documents Analysis

Analyses of the Corresponding Author's Country, Author Impact, Source Local Impact, and Most Local Cited Documents have been conducted. In the analysis of the corresponding author's country, the total number of publications (TNP), single and multiple-country publications (SCP & MCP), and the multiple-country publication ratio (MCP Ratio) have been calculated. The MCP Ratio represents the proportion of articles involving authors from multiple countries relative to the total number of articles. The tables and figures in the analyses are constructed based on the h, g, and m index values.

Variables in the analyses include Year of Publication (YP), YYP= Year 2023-Year of Publication, Global Citations (GC), Local Citations (LC), the ratio of LC to GC (LC/GC), annual local citations (LC/YYP), and annual global citations (GC/YYP). LC represents the number of citations an article receives from other articles examined in the analysis, whereas GC represents the number of citations an article receives from all articles indexed in the Web of Science (WoS).

Authors Keyword Analysis

In this analysis, a word cloud has been generated.

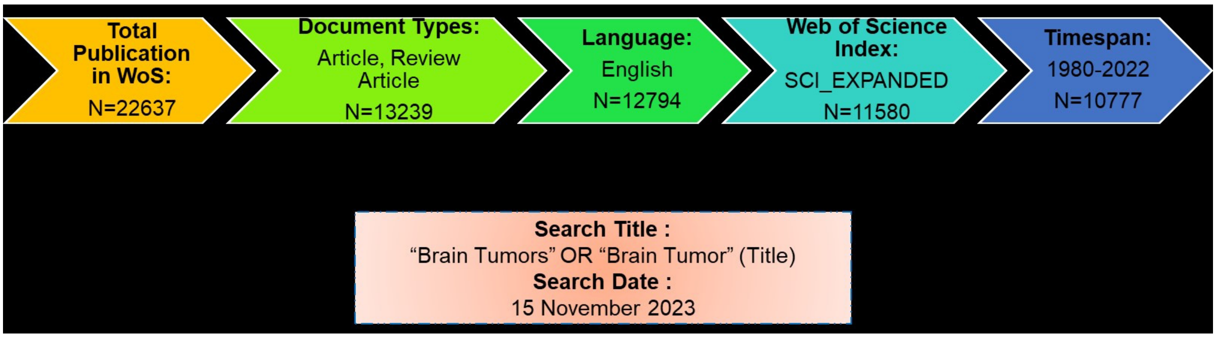

Fig. 1. **Data collection and analysis process.**

The most frequently used top 50 keywords have been included in the analysis. A trend topic analysis has been conducted to identify the keywords' initial usage and peak frequency times. For this analysis, keywords used at least five times a year have been selected.

Another analysis under this topic is the 'co-occurrence network of authors' analysis, which was carried out with 39 keywords. In the analysis, clusters consisting of circles in different colors are formed. A circle represents each keyword. The size of the circle is directly proportional to the frequency of use of the keyword, while the thickness of the lines connecting the circles is directly proportional to the co-occurrence frequency of the keywords.

Thematic Analysis

The research period (1980-2022) has been divided into four sub-periods based on the number of documents. These sub-periods are designated as 1980-1999, 2000-2012, 2013-2020, and 2021-2022. Thematic analysis was conducted using 2000 keywords. The most recurrent keywords have been clustered into thematic groups. The two most frequently recurring words represent each cluster. The size of the circles is proportional to the frequency of use of the keywords they represent. The thematic or strategic diagram is divided into four quadrants. Each quadrant has been analyzed in terms of centrality and density. Density is represented along the y-axis, while centrality is represented along the x-axis. Centrality denotes the significance of the theme, while density indicates its development. The four quadrants of the thematic diagram are Motor Themes, Niche Themes, Emerging or Declining Themes, and Basic Themes.

Motor Themes: Located in the top right quadrant of the thematic diagram. They indicate high density and centrality. These are significant themes.

•Niche Themes: Situated in the bottom right quadrant of the diagram. They represent high density but low centrality. These are themes that have lost significance and are isolated.

•Emerging or Declining Themes: These are found

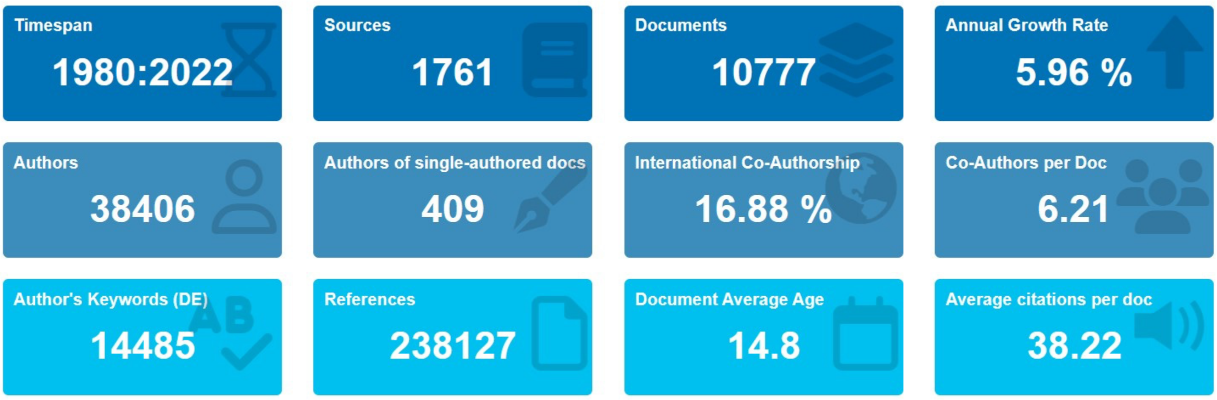

Fig. 2. **Main information.**

in the top left quadrant of the diagram. They denote low density and centrality. These are themes that are either newly emerging or declining in importance.

•Basic Themes: Positioned in the bottom left quadrant of the diagram. These themes have low density but high centrality. They are seriously researched themes and form the main focus of the studies.

A Thematic Evolution Map covering four periods has been created to analyze theme changes over the years. The size of the nodes indicates the multitude of keywords, while the flow lines between nodes depict the direction of evolution of the thematic clusters.

Collaboration Network Analysis

Authors, Institutions, and Countries Collaboration Network analyses have been conducted in this analysis. Each author, institution, or country is represented in the figures by a circle. Those collaborating have formed clusters in distinct colors. The size of the circle and the thickness of the lines connecting the circles are directly proportional to the collaboration intensity of the author, institution, or country.

RESULTS

Structure Analysis

The foundational data is presented in Fig. 2. The articles have been published in 1761 journals. The annual increase in the number of articles is 5.96%. A total of 38,406 authors have penned these articles. The rate of international author collaboration stands at 16.88%. In these articles, 14,485 keywords and 238,127 references have been employed. The average citation per article is 38.22.

In Brain Tumors, the annual numbers of academic articles produced between 1980 and 2022 are presented in Fig. 3. The increase in the number of annual articles is noteworthy. The quantity of articles has continuously escalated, and this surge in volume has particularly intensified since the mid-2000s. The increase taken after the year 2018 is particularly noteworthy.

Countries, Authors, Sources, Documents Analysis

The countries of the authors of the analyzed articles and the number of articles are presented in Fig. 4. Authors from the USA exhibit a distinct superiority. However, the MCP Ratio value for US authors is low. This indicates a lower level of international collaboration among US authors. Chinese authors rank second regarding the number of articles, but their MCP Ratio values are higher. The contribution of Chinese authors to international collaborations is more significant. European countries also contribute considerably to article production, and their MCP Ratio values are high. The h, g, and m-index, TC, NP, and PY-Start values of the top 20 authors are presented in Table 1. The highest h and g-index values belong to Kun LE, followed by

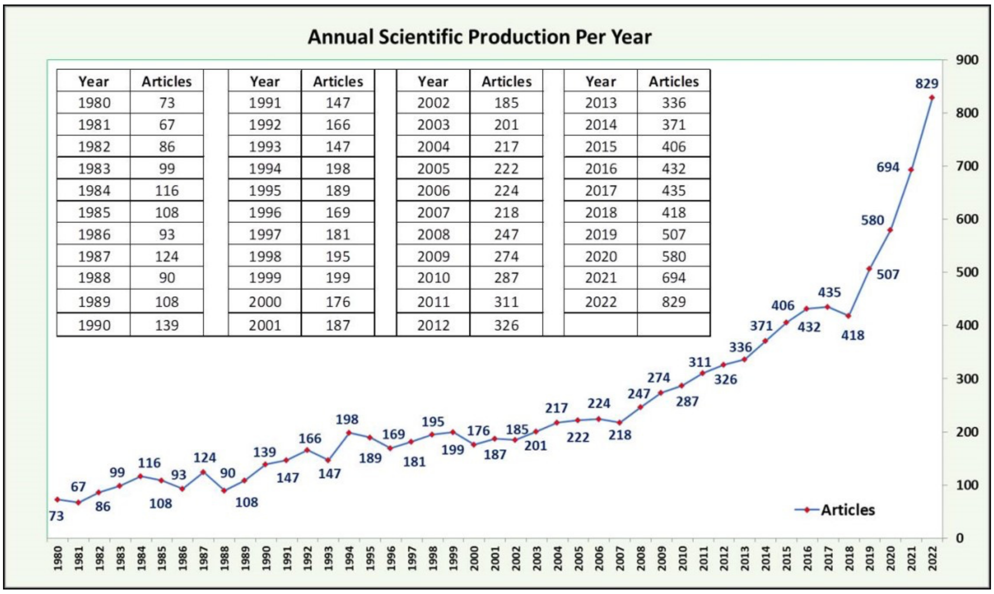

Fig. 3. Annual scientific production per year.

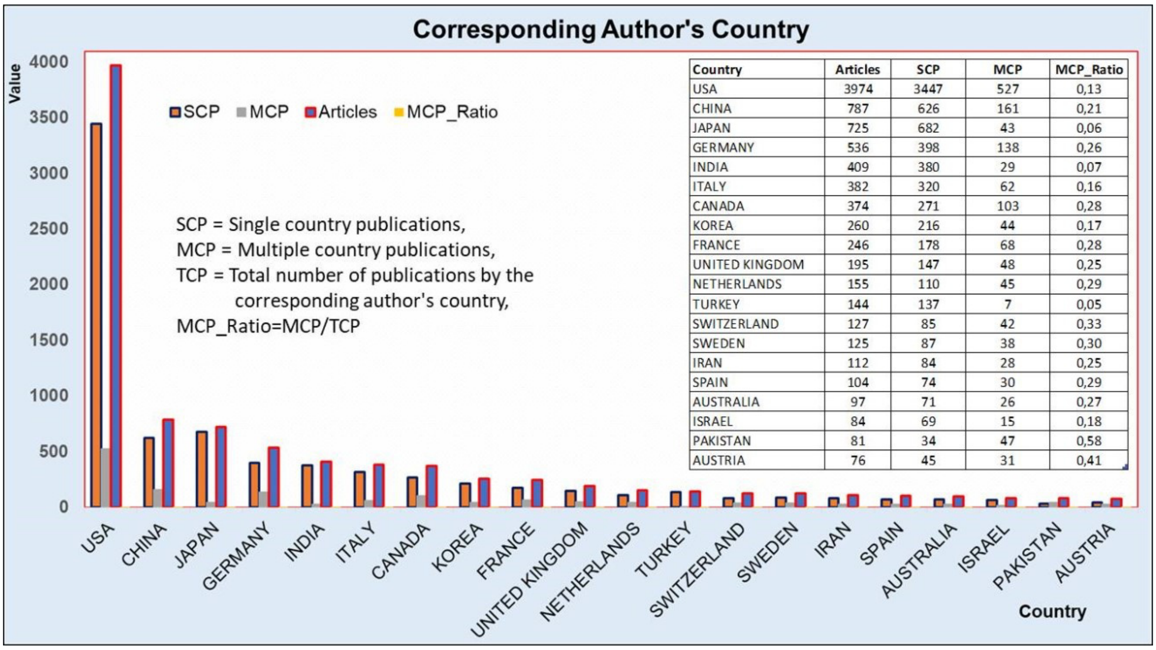

Fig. 4. **Corresponding author's country.**

Table 1. **Author impact**

Author	H-index	G-index	M-index	TC	NP	PY-start
Kun LE	38	62	0.927	4402	62	1983
Black PM	36	59	1.059	4472	59	1990
Wen PY	33	44	1.031	3744	44	1992
Gajjar A	31	54	1.069	4914	54	1995
Prados MD	31	43	0.838	2916	43	1987
Berger MS	30	45	0.769	3481	45	1985
Black KL	30	47	0.857	2797	47	1989
Friedman HS	30	50	0.75	3699	50	1984
Packer RJ	30	51	0.833	3573	51	1988
Barth RF	29	39	0.879	2641	39	1991
Bigner DD	29	52	0.659	3173	52	1980
Boyett JM	28	40	0.718	2914	40	1985
Brem H	27	40	0.614	2015	40	1980
Chang SM	27	42	0.931	2428	42	1995
Goldman S	27	48	1	2489	48	1997
Pollack IF	26	40	0.867	2503	40	1994
Sawaya R	26	37	0.634	1905	37	1983
Yung WKA	26	37	0.65	2452	37	1984
Fouladi M	24	36	0.96	2376	36	1999
Merchant TE	24	41	0.923	2100	41	1998

NP=Number of publications, TC=Total citations, PY-start=Publication year starting

Table 2. Source local impact

Source	H-Index	G-Index	M-Index	TC	NP	TC/NP	PY-start
Cancer Research	74	141	1.68	20435	173	118.1	1980
Journal of Neurosurgery	66	100	1.50	13712	273	50.2	1980
Journal of Neuro-oncology	63	93	1.58	18101	589	30.7	1984
Neuro-oncology	63	100	2.63	12601	216	58.3	2000
Journal of Clinical Oncology	61	93	1.49	10537	93	113.3	1983
Neurosurgery	60	98	1.36	11669	206	56.6	1980
Cancer	53	91	1.21	8672	122	71.1	1980
American Journal of Neuroradiology	49	86	1.11	7711	121	63.7	1980
Clinical Cancer Research	44	72	1.52	6769	72	94,0	1995
Journal of Nuclear Medicine	43	78	1.02	6792	78	87.1	1982
ActaNeuropathologica	42	70	0.96	5049	76	66.4	1980
International Journal of Radiation Oncology, Biology, Physics	38	74	0.86	5831	107	54.5	1980
International Journal of Cancer	37	63	0.90	4001	66	60.,6	1983
Radiology	35	52	0.83	5207	52	100.1	1982
Magnetic Resonance in Medicine	34	69	0.92	4819	70	68.8	1987
Plos One	34	52	2.00	3219	104	31.0	2007
Proceedings of the National Academy of Sciences	30	32	0.91	6979	32	218.1	1991
Neurology	29	41	0.71	3549	41	86.6	1983
Childs Nervous System	28	39	0.72	2315	124	18.7	1985
Oncogene	28	37	0.85	2435	37	65.8	1991

NP=Number of publications, TC=Total citations, TC/NP=Citations per paper, PY-start=Publication year starting

Black PM. The author who has reached the highest m-index value is Gajjar A, followed by Black PM and Wen PY.

Table 2 presents the top 20 journals ranked by their H-index values. These journals have collectively published 24.61% of the total articles. The highest h and g-index values belong to Cancer Research. Neuro-Oncology holds the distinction of having the highest m-Index value. Cancer Research also leads in terms of the total number of citations received. The highest TC/NP value source is the Proceedings of the National Academy of Sciences of the United States of America.

The top 20 articles with the highest LC values are presented in Table 3. The most recent publications include Sajjad M, 2019; Deepak S, 2019; and Anaraki AK, 2019. The oldest article is by Libermann TA and is dated 1985. Havaei M, 2017, authors the article with the highest LC value, while the one with the highest GC value is by Singh SK, 2003. The paper by Havaei M, 2017 also stands out for having the highest LC/YYP and GC/YYP values. Regarding the LC/GC Ratio, the article by Anaraki AK, 2019, has emerged as particularly noteworthy.

Authors Keyword Analysis

In Fig. 5, the articles' top 50 most frequently used keywords are presented as a word cloud, and the top 20 are shown in a frequency table. The keyword 'Brain Tumors' is often used so predominantly that it can obscure other keywords in the word cloud.

Therefore, to avoid this overshadowing, 'Brain Tumors' is not displayed in the word cloud. The keywords with the highest frequency among authors are 'Brain tumors,' 'Glioma, ' ' glioblastoma,' and 'Magnetic resonance imaging.' Fig. 6 illustrates the trend of these keywords over the years. Between 1993 and 1995, the keywords 'Autoradiography,' 'Bromodeoxyuridine,' 'Thymidine Kinase,' 'Hyperthermia,' 'Bcnu,' and 'Ganciclovir' were more prevalent, whereas in recent times, terms like 'Brain Tumor Classification,' 'Brain Tumor Detection,' 'Deep Learning,' 'Brain Tumor Segmentation,' 'Classification,' and 'Neuro-Oncology' have gained more prominence.

In the context of medical research, the utilization of specific terminologies peaked in certain years: "Brain Tumors" in 2014, "Glioma" in 2013, "Glioblastoma" in 2016, and "Magnetic Resonance Imaging" in

Table 3. Most local cited documents

Document	YP	LC	LC/YYP	GC	GC/YYP	LC/GC Ratio%
Havaei M, 2017, Med Image Anal	2017	262	43.667	1690	281.667	15.50
Pereira S, 2016, Ieee T Med Imaging	2016	245	35.000	1364	194.857	17.96
MenzeBH, 2015, IeeeT Med Imaging	2015	239	29.875	1846	230.750	12.95
DeangelisLM, 2001, New EnglJMed	2001	141	6.409	1347	61.227	10.47
Bauer S, 2013, PhysMed Biol	2013	140	14.000	527	52.700	26.57
Singh SK, 2003, Cancer Res	2003	135	6.750	3918	195.900	3.45
Zhao XM, 2018, Med Image Anal	2018	122	24.400	440	88.000	27.73
KleihuesP, 1993, Brain Pathol	1993	120	4.000	1371	45.700	8.75
HemmatiHD, 2003, P NatlAcadSciUSA	2003	106	5.300	1429	71.450	7.42
GlantzMJ, 2000, Neurology	2000	96	4.174	544	23.652	17.65
DuffnerPK, 1993, New EnglJ Med	1993	95	3.167	583	19.433	16.30
SajjadM, 2019, JComputSci-Neth	2019	86	21.500	334	83.500	25.75
Deepak S, 2019, ComputBiol Med	2019	85	21.250	381	95.250	22.31
PrastawaM, 2004, Med Image Anal	2004	83	4.368	387	20.368	21.45
ZacharakiEI, 2009, MagnResonMed	2009	81	5.786	491	35.071	16.50
TaphoornMJBb, 2004, Lancet Neurol	2004	77	4.053	488	25.684	15.78
LibermannTA, 1985, Nature	1985	76	2.000	1412	37.158	5.38
GordilloN, 2013, MagnReson Imaging	2013	76	7.600	408	40.800	18.63
AnarakiAK, 2019, BiocybernBiomed Eng	2019	74	18.500	224	56.000	33.04
Calabrese C, 2007, Cancer Cell	2007	73	4.563	1661	103.813	4.39

YP=Year of publication, YYP=Year 2023-year of publication, GC=Global citations, LC=Local citation

Terms	Frequency
brain tumors	2923
glioma	835
glioblastoma	476
magnetic resonance imaging	284
mri	268
medulloblastoma	246
brain neoplasms	221
meningioma	201
brain	196
deep learning	188
cancer	172
chemotherapy	171
brain tumor segmentation	167
astrocytoma	166
pediatric	165
blood-brain barrier	159
children	158
oncology	141
segmentation	141
radiotherapy	139

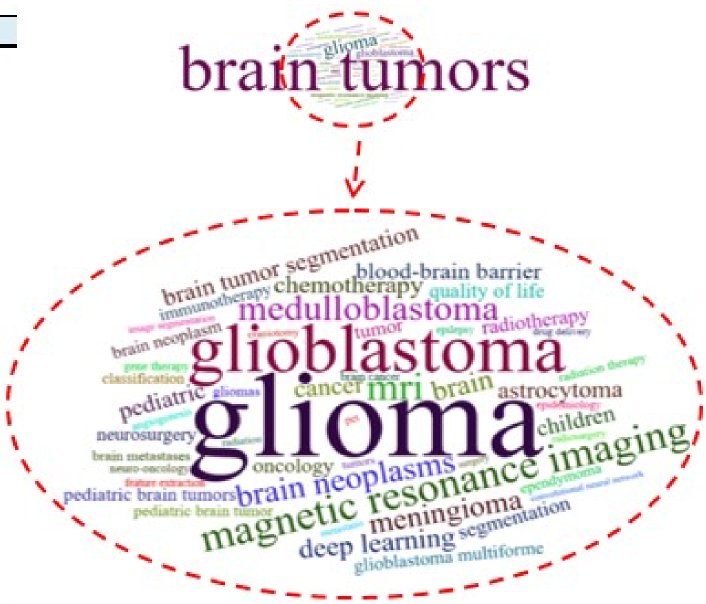

Fig. 5. Word cloud, and frequency table.

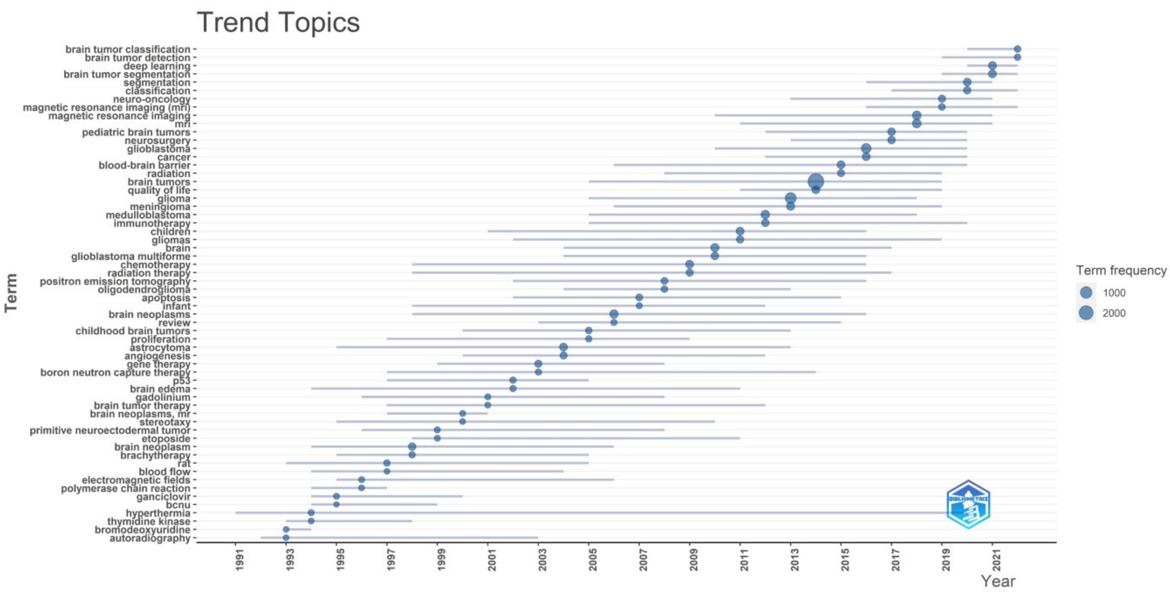

Fig. 6. Trend topics.

2018. Fig. 7 presents a co-occurrence network of the top 50 keywords.

These keywords are clustered into three distinct groups. The red cluster represents "Brain Tumors," while the blue cluster indicates "Glioma." The green cluster, however, does not have a dominant keyword. The red cluster can be characterized as "Neuro-Oncology and Brain Tumor Research," the blue as "Brain Tumor Subtypes and Therapies," and the green as "MRI-based Brain Tumor Analysis and Segmentation." The most robust connections within this network are observed between Brain Tumors-Glioma, Brain Tumors-MRI, Brain Tumors-Glioblastoma, Brain Tumors-Pediatric, Glioma-Meningioma, and Glioma-Glioblastoma. The size of the circles in the network graphically represents the frequency of usage of each

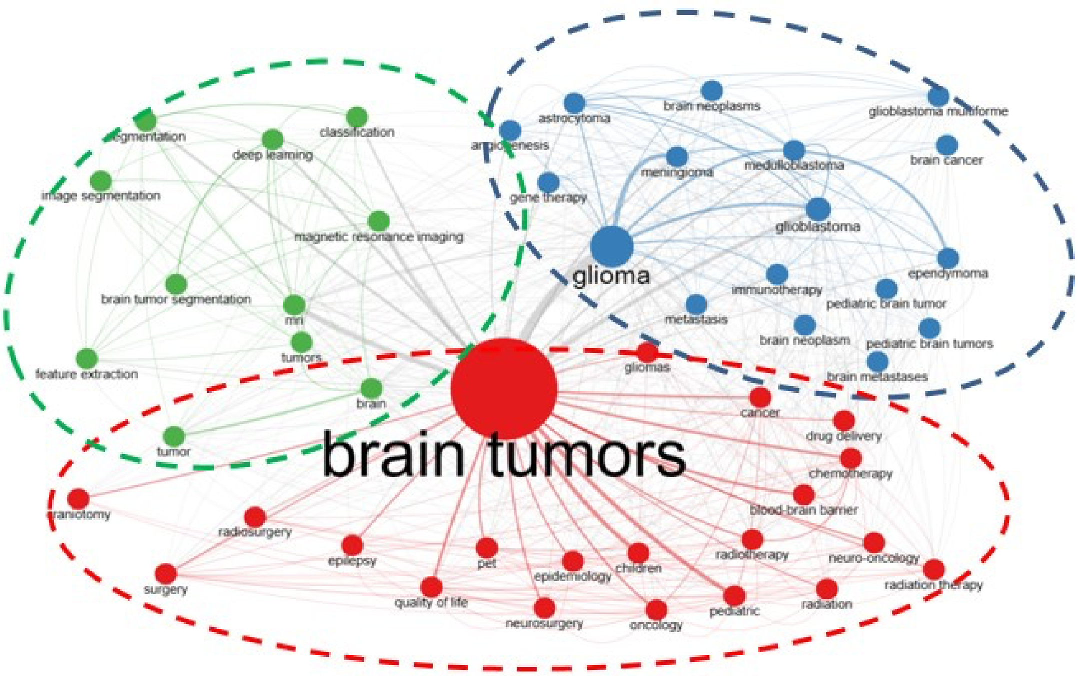

Fig. 7. Co-occurrence network.

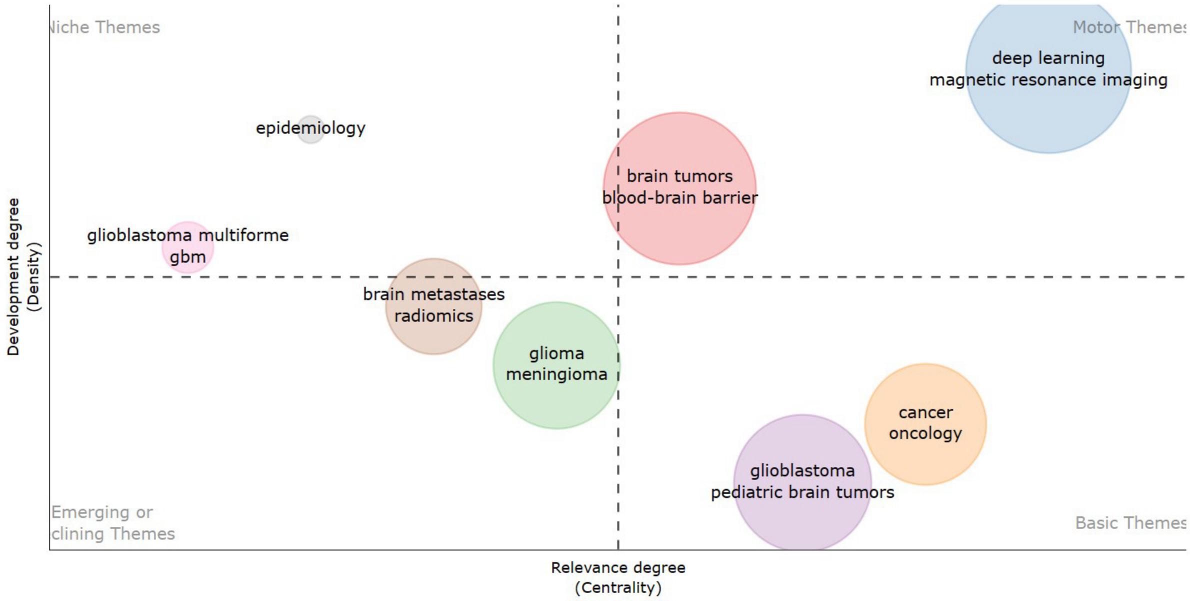

Fig. 8. Thematic map (2021-2022).

keyword, while the thickness of the lines connecting these keywords correlates with the frequency of their co-occurrence.

Thematic Analysis

For thematic analysis, the period from 1980 to 2022 has been subdivided into four sub-periods. Thematic maps have been created for these periods. The thematic map covering 2021 and 2022 has been shared (Fig. 8). During 2021-2022, 'Deep Learning' and 'Brain Tumors' formed the motor themes, while 'GlioblastomaMultiforme' and 'Epidemiology' represented the niche themes. Additionally, 'Glioma' and 'Brain Metastases' emerged as emerging themes, with 'Cancer' and 'Glioblastoma' constituting the basic themes.

In addition to Thematic Maps, a four-period Thematic Evolution Mapping has been created to examine the changes and developments of themes over the years (Fig. 9). According to this, during the 2021-2022 period, themes such as Brain Tumors, Glioma, GlioblastomaMultiforme, Deep Learning, Epidemiology, and Cancer Brain Metastases have emerged. The Brain Tumors theme has been informed and enriched

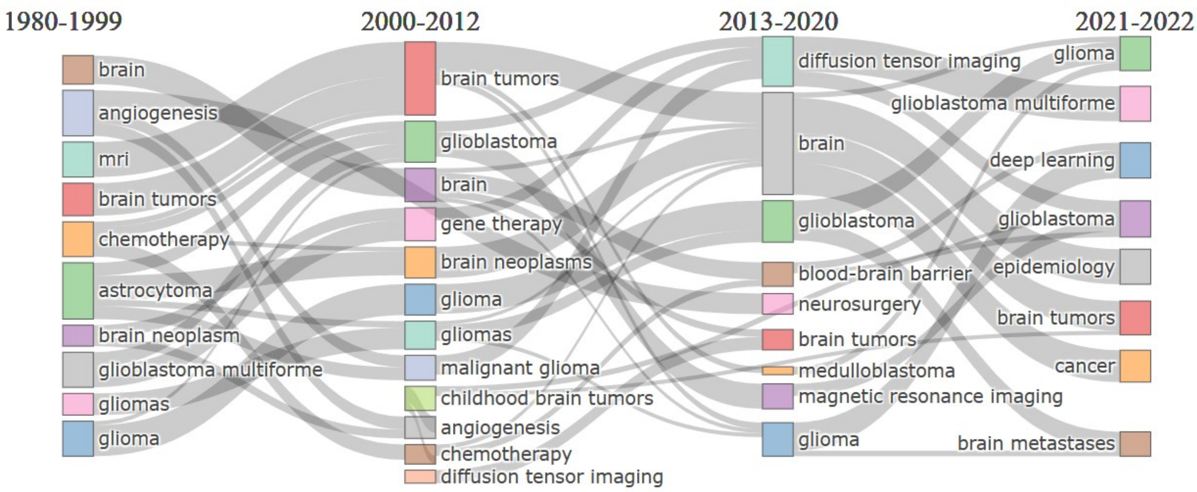

Fig. 9. Thematic evolution map (1980–2022).

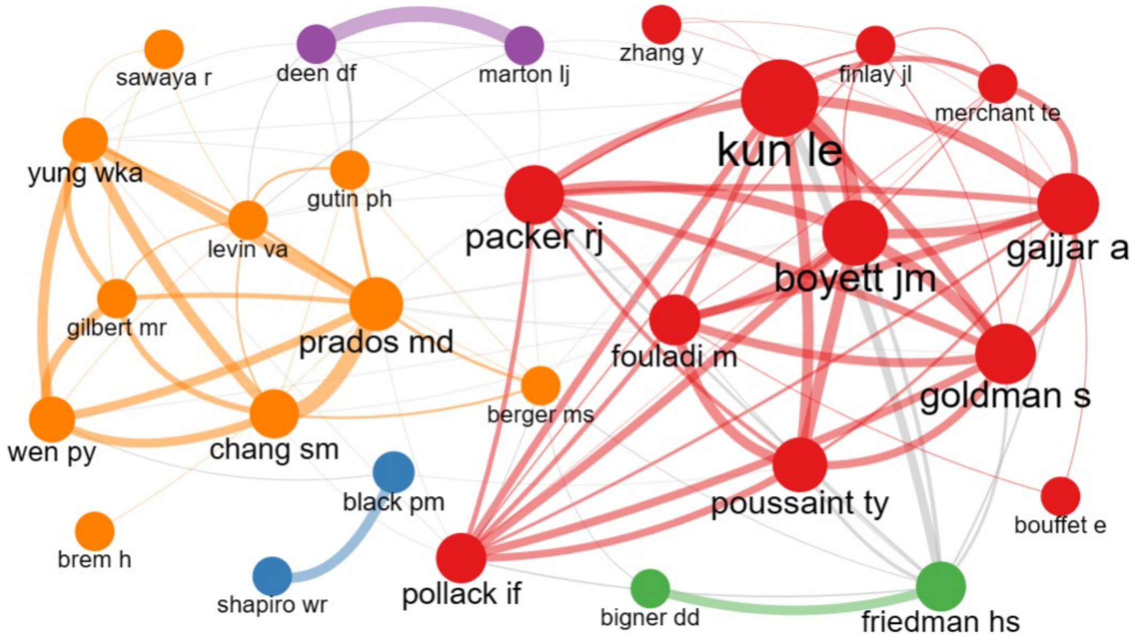

Fig. 10. Authors collaboration network.

by sub-themes, including Brain, Childhood, and Brain Tumors.

Collaboration Network

The authors' collaboration network is depicted in Fig. 10.

Each circle in the figure represents an author. It is observed that the authors are grouped into five clusters. The cluster with the highest number of authors, containing 12, is the red cluster. Kun LE is the author with the most collaborations. Following Kun LE, the authors with the most collaborations are Boyett JM,

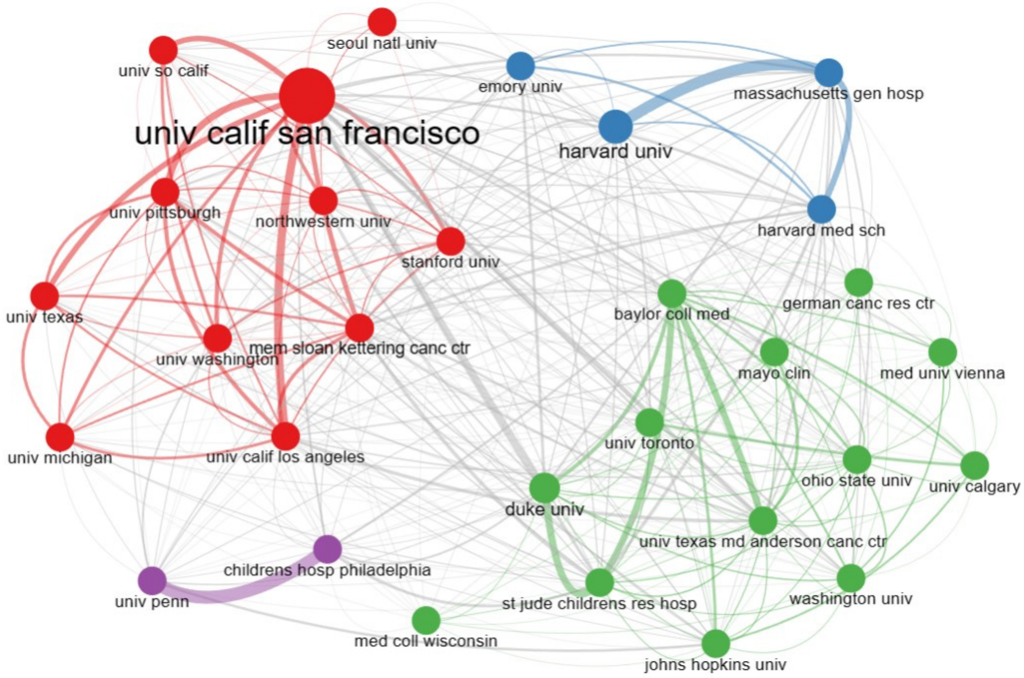

Fig. 11. Institutions collaboration network.

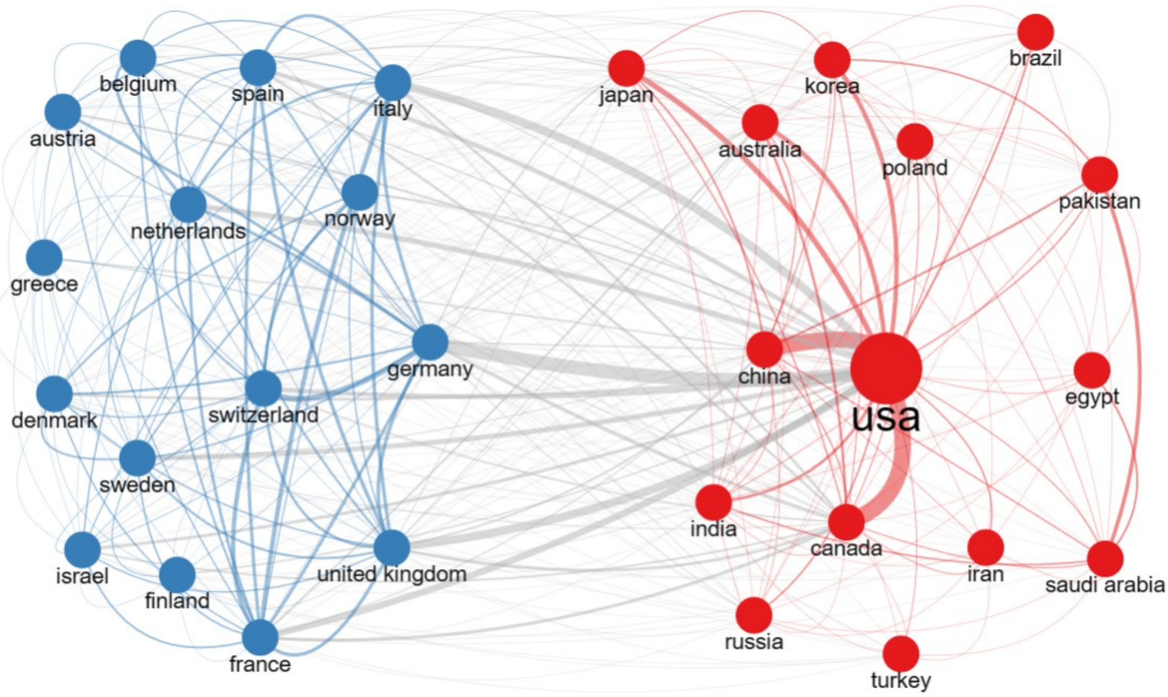

Fig. 12. **Countries collaboration network**

Packer RJ, and Gajjar A. The Institutions Collaboration Network is shown in Fig. 11.

The top 30 institutions were considered, and the Louvain Algorithm was used. The institutions have formed four clusters. Institutions within the same color clusters collaborate in publishing articles. The institution with the most collaborations is the University of California San Francisco, followed by Harvard Univ. As indicated by the thickness of the lines, the institutional pairs with the most collaborations are Univ Penn – Children Hosp Philadelphia, Harvard Univ – Massachusetts Gen Hosp, and Baylor Coll Med – ST Jude Children Res Hosp. The results of the Countries Collaboration Network are presented in Fig. 12.

The top 30 countries were considered, and the Louvain Algorithm was used. Two clusters have formed. The red cluster includes 15 countries, while the blue cluster includes 5. The red cluster is more centralized and centered around the USA's collaboration. The countries with the most collaborations are USA - Canada, USA - China, and USA - Germany.

DISCUSSION

Science mapping is the process of analyzing and visualizing a scientific subject. This analysis and visualization can encompass scientific studies, articles, and other academic resources. Through this technique, the main and sub-topics in a broad research field, the interrelationships and trends among them, and significant developments and connections can be discerned. Methods such as text mining and data visualization are encompassed within the scope of science mapping. Bibliometric analysis examines the literature macroscopically and presents a projection. Therefore, those wishing to track the scientific outputs in a research field and their developmental process prefer this analysis method [5].

Eugene Garfield has made significant contributions to the field of scientometrics. He is one of the most pivotal figures in the field of scientometry. Garfield laid the foundation that led to the WoS, today one of the most crucial platforms for citation and analytical information searching. It serves not only as an academic library but also as a rich dataset. WoS encompasses innumerable citation links and metadata, expanding daily. WoS is a comprehensive and international bibliographic database, making it the most efficacious bibliographic data source for conducting bibliometric and similar analyses [6]. Our use of the Web of Science (WoS) in our analyses is significant for these reasons. Consequently, our data are highly reliable.

The Bibliometrix program was used for the analysis of the data. This program is an open-source software developed on R-based science mapping. The R programming language originated in the 1990s and has become a fundamental computational tool for research in various fields, from statistics to medicine. One of its key features is facilitating learning through producing meaningful graphics [7, 8]. In our study, we have utilized this program feature to visualize the topic of brain tumors with rich graphics.

Our study's analyses of countries, authors, sources, and documents have been based on the h, g, and m indices. The h (Hirsch) index reflects a scenario where an author has at least an "h" number of papers, each receiving at least "h" citations. The h-index analyzes a researcher's cumulative scientific impact. It examines a researcher's productivity and citations and measures it as a single number. It is a reliable and robust indicator of scientific success. In addition to individual assessments, medical journals, publishers, institutions, and universities can also be evaluated with the h-index [9]. The G index aims to represent the distribution of citations better. The G-index has been developed to measure global citation performance more accurately. Its advantage is that it highlights articles that receive numerous citations. Therefore, more weight is given to highly cited articles [10]. The m-index is a version of the h-index. The h-index increases with the length of a career. The m-index has been developed to facilitate comparisons among academics with varying lengths of academic careers. In comparing researchers with varying lengths of careers, this can be utilized to mitigate the effects of time [9].

This study presents detailed statistical information on articles related to brain tumors. Within this scope, 1,761 sources, 10,777 documents, and 38,406 authors have been examined. The number of single-authored documents is 409. The frequency of international co-authorship is approximately 17%, while the co-author per document is 6.21. The average age of documents is around 15%, and the average citations per document are 38.22.

It has been determined that studies on brain tumors have increased steadily over the years. This is supported by the advancements recorded in the medical field. However, it is noteworthy that there has been a significant increase in the annual number of articles published after 2018. Undoubtedly, this increase is influenced by the classification of central nervous system tumors by the World Health Organization in 2021 [11] and the inclusion of some new tumors in this classification [12]. Similarly, the role of immunotherapy studies and bioinformatics in this increase is notable [1]. In recent years, studies related to technologies such as deep learning and machine learning, which have become widespread in the medical field, also have a significant share in this increase [13, 14].

The highest h and g-index values belong to Kun LE and Black PM, respectively. The highest m-index value belongs to Gajjar A. Professor Larry E. Kun, after an extensive and fruitful career in the field of radiation oncology, passed away in 2018. He served in significant institutions such as the American Society for Radiation Oncology, the American Board of Radiology, and research hospitals. Professor Peter M. Black is a neurosurgeon. He is engaged in the field of neurosurgery at Brigham and Women's and Children's Hospital and Harvard Medical School. He is a member of the Congress of Neurological Surgeons and the World Federation of Neurosurgical Societies. Professor Amar Gajjar is affiliated with St. Jude Children's Research Hospital. He was honored with the Scott and Tracie Hamilton Endowed Chair in Brain Tumor Research.

The most effective journal is Cancer Research, published by the American Association for Cancer Research. Its impact factor is 11.3. It is indexed in numerous databases. Its TC/NP (Total Cites/Number of Papers) value is also very high. Regarding h-index and g-index values, the second journal is the Journal of Neurosurgery, the official publication of the American Association of Neurological Surgeons. Its impact factor is 4.1. The highest m-index value belongs to Neuro-Oncology, the official publication of the Neuro-Oncology Society. It is also affiliated with the Japan Neuro-Oncology Society and the European Neuro-Oncology Society. Its impact factor is 15.9.

The article by Havaei M, 2017 [15] holds the highest LC value, while the highest GC value belongs to the article by Singh SK, 2003 [16]. Both articles discuss significant developments relevant to their respective years of publication. The subject of Havaei M, 2017 is glioblastomas, specifically related to a brain tumor segmentation method based on deep neural networks. Deep neural networks are among the most significant applications of artificial intelligence in our daily lives [17]. This study is particularly programmed with the deep neural network machine learning method adapted for image data [15]. The article by Singh SK, 2003 reports identifying and purifying a cancer stem cell from human brain tumors of different phenotypes. The stem cell was isolated by expressing the surface marker CD133. Stem cells are used in researching tumor development and treatments.

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The most frequently used keywords drawing significant attention include glioma, glioblastoma, magnetic resonance imaging, medulloblastoma, and deep learning. The most common primary brain tumor originates from glial cells, known as Glioma [18]. Glioblastoma, a type of glioma, is the most common and aggressive malignant brain tumor [18]. In recent years, studies have increased, particularly on Gliomas and Glioblastomas. Immunotherapy, encompassing methods like cancer vaccines, oncolytic viruses, and immune checkpoint inhibitors, has recently become a significant option in Glioblastoma treatment [19]. Medulloblastoma is the most common embryonal tumor of the central nervous system in childhood [20]. There have been advancements in its treatment in recent years. Multimodal treatment and appropriate risk stratification have increased long-term survival rates across all ages [20]. Deep learning, a branch of artificial intelligence, is one of today's fundamental technologies based on artificial neural networks [21]. It is rapidly becoming widespread in healthcare services, especially visual recognition [21]. Numerous studies have been conducted on using this technology for diagnosing brain tumors [22-24]. According to the trend topics analysis results, the frequently used keywords mentioned above have become trend topics in recent years. In addition, 'brain tumor classification' has also emerged as a trending topic in recent years. This may be due to the Classification of Tumors of the Central Nervous System study conducted by the WHO in 2021. Numerous articles related to the study have been published in recent years [25-27].

In the thematic map derived from recent studies, the dominant themes are deep learning, magnetic resonance imaging, brain tumors, and the blood-brain barrier. Deep learning is used in magnetic resonance imaging to detect brain tumors at an early stage [22-24]. The blood-brain barrier poses a challenge in delivering therapeutics to the brain and tumor, with some brain tumors producing a blood-tumor-barrier [28]. Research to overcome these barriers to enhance the effects of anti-cancer treatments has become popular in recent years [29-30].

Upon examining thematic maps from all periods, it is assessed that the likely topics and scopes of future research on brain tumors will be biomarkers, personalized treatments, artificial intelligence, immunotherapy, and pediatric brain tumors.

Limitations

This bibliometric analysis of brain tumor research over four decades has notable limitations. Its dependence on bibliographic databases can lead to selection biases, excluding non-indexed and grey literature that might contain important contributions. While citation metrics indicate academic influence, they don't capture the clinical relevance of research. Additionally, evolving terminologies and indexing standards may complicate keyword normalization. However, the study's strength lies in its methodological rigor and visualization of thematic trends. Future research should consider alternative impact indicators, use machine learning for semantic analysis, and include diverse scholarly contributions. The Bibliometrics program may make mistakes in the analysis of some expressions. In our study, the expressions "magnetic resonance imaging" and "mri" were evaluated as two different concepts.

CONCLUSION

In conclusion, this bibliometric analysis of brain tumor research over the past four decades represents a seminal contribution to the scientific understanding of global research trends, intellectual structure, and emerging thematic frontiers within the field. Through the rigorous application of science mapping methodologies, this study unveils pivotal shifts in research foci, influential scholarly networks, and the evolution of key conceptual frameworks that have shaped contemporary neuro-oncology. The originality of this work lies in its comprehensive synthesis of an extensive body of literature, offering an unprecedented panoramic view of scientific progress while identifying critical knowledge gaps and future research trajectories. By illuminating the intricate interplay between innovation, collaboration, and knowledge dissemination, this study not only advances bibliometric scholarship but also provides an indispensable reference for researchers, policymakers, and funding bodies seeking to optimize research strategies in the relentless pursuit of breakthroughs in brain tumor diagnosis, treatment, and patient outcomes.

Ethical Statement

Ethical approval is not required for this study. There are no human or animal elements in our study. Obtained from open sources on the internet.

Authors' Contribution

Study Conception: TK; Study Design: TK; Supervision: TK; Funding: TK; Materials: TK; Data Collection and/or Processing: TK; Statistical Analysis and/or Data Interpretation: TK; Literature Review: TK; Manuscript Preparation: TK and Critical Review: TK.

Conflict of interest

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