Exploring diseases and syndromes in neurology case reports from 1955 to 2017 with text mining

Amir Karami[a,*], Mehdi Ghasemi[b], Souvik Sen[c], Marcos F. Moraes[d], Vishal Shah[d]

[a] College of Information and Communications, University of South Carolina, USA
[b] Department of Neurology, Brigham and Women's Hospital, Harvard Medical School, USA
[c] Neurology Department, School of Medicine, University of South Carolina, USA
[d] Computer Science and Engineering Department, University of South Carolina, USA

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ABSTRACT

Background: A large number of neurology case reports have been published, but it is a challenging task for human medical experts to explore all of these publications. Text mining offers a computational approach to investigate neurology literature and capture meaningful patterns. The overarching goal of this study is to provide a new perspective on case reports of neurological disease and syndrome analysis over the last six decades using text mining.
Methods: We extracted diseases and syndromes (DsSs) from more than 65,000 neurology case reports from 66 journals in PubMed over the last six decades from 1955 to 2017. Text mining was applied to reports on the detected DsSs to investigate high-frequency DsSs, categorize them, and explore the linear trends over the 63-year time frame.
Results: The text mining methods explored high-frequency neurologic DsSs and the relationships between them from 1955 to 2017. We detected more than 18,000 unique DsSs and found 10 categories of neurologic DsSs. While the trend analysis showed the increasing trends in the case reports for top-10 high-frequency DsSs, the categories had mixed trends.
Conclusion: Our study provided new insights into the application of text mining methods to investigate DsSs in a large number of medical case reports that occur over several decades. The proposed approach can be used to provide a macro level analysis of medical literature by discovering interesting patterns and tracking them over several years to help physicians explore these case reports more efficiently.

1. Introduction

Medical publications have been considered as primary sources to report findings in different fields such as neurology. The first line for reporting clinical evidence has been in medical case reports that contain single or multiple cases. Medical case reports (MCRs) usually represent rare cases that are the only evidence before published trials [1]. MCRs are "a formal summary of a unique patient and his or her illness, including the presenting signs and symptoms, diagnostic studies, treatment course and outcome" [2], and are sometimes the first reportage of new discoveries [3]. However, there is no standard format for MCRs and it is difficult to get a macro level perspective [3]. Moreover, MCRs have been historically considered as a cost- and time-effective method in advancing knowledge and education from both patient and physician perspectives with direct impact on clinical

practice and patient care [4]. They have several benefits including the presentation of new applications, discussion of new diseases and syndromes (DsSs), generation of hypotheses and novel solutions, and providing educational value to the medical professions [3]. In the late 1990s, interest in MCRs grew. For example, the Lancet introduced a peer-reviewed "Case Reports" section and some new journals were launched for the sole purpose of publishing MCRs [3].

The increasing number of published neurology case reports makes the macro level analysis almost impossible because it is a challenge for researchers to keep up-to-date with published medical case reports. Moreover, the number of case series is far fewer than the number of single case reports [5]. This issue requires a new approach to review neurology case reports with respect to DsSs entities. Our objective analysis detects high-frequency DsSs and the relationships between DsSs to overcome the generalization barrier in exploring MCRs. In

* Corresponding author. Davis College, 1501 Greene St, Columbia, SC, 29208, USA.
E-mail addresses: karami@sc.edu (A. Karami), m82.ghasemi@gmail.com (M. Ghasemi), souvik.sen@uscmed.sc.edu (S. Sen), mmoraes@email.sc.edu (M.F. Moraes), vshah@email.sc.edu (V. Shah).

addition, analyzing numerous MCRs is an opportunity for comparison and new hypothesis generation.

Thus, in the present study, we tried to reduce the gap between the traditional case report analysis and qualitative-quantitative research methods. There are more than 2 million case reports in the PubMed database,[1] but this database and other similar platforms don't provide data analytics features. There are several MCR surveys that consider a small sample of publications, such as analysis of 100 cases in dermatology to evaluate the content quality of the cases [6], exploration of 435 dental cases to detect bias [7], review of 130 drug safety cases [8], and review of 106 published case reports in *The Lancet* [1].

In neurology, traditional case series analysis has been developed to investigate specific issues such as analyzing 100 antibodies cases to investigate the effects of antibodies on N-methyl-D-aspartate (NMDA) receptors [9], examining the frequency of associated tumors and concurrent neuronal autoantibodies on 20 patients [10], investigating 28 case series with total of 177 patients published between 2000 and 2007 to examine the relationship of pathological gambling, dopamine agonists, and dopamine dysregulation syndrome [11], analyzing the accuracy of the factors applied in diagnosing Alzheimer's disease for 134 patients with memory complaints [12], detecting the causes of cerebral palsy and their relative frequency in 217 cases between 1991 and 2001 [13], characterizing 1377 pediatric patients with intracranial aneurysms between 1991 and 2004 [14], and developing a survey with 99 cases to determine the proportion of patients using tracking technologies [15].

Analyzing a large number of case reports is a time-consuming and labor-intensive process. Therefore, applying text mining methods to identifying patterns from corpora offers promise. Among different text mining methods, topic modeling has been considered in a wide range of applications. The goal of topic modeling is to detect and group related words for the purpose of organizing and understanding documents in a corpus. This type of computational analysis is an effective and efficient approach to get a macro level view of medical case reports. Analysis of case report entities such as DsSs can provide a granular perspective of the case report studies. To fill the gap in the related literature landscape, we investigated the DsSs in the neurology case reports.

In the present study, we applied text mining and trend analysis on the neurology case reports to (1) investigate high-frequency DsSs; (2) detect and categorize DsSs; and (3) explore the overall and yearly trends of the high-frequency DsSs and their categories during this research time frame. This study has research and educational applications for the experts who are interested in exploring neurological DsSs and their relationships in medical case reports.

The contributions of this paper are three-fold. First, the proposed framework offers a fully functional and automated approach to investigate a large number of the existing medical case reports and their overall trends during six decades. Research managers and policymakers can utilize our approach to understand the landscape of the neurology case reports. Secondly, the objective nature and the publicly available data of this research makes it easier to replicate the results using the shared data. Thirdly, this is the first research that finds the interactions between DsSs and discloses the patterns in a dataset containing rare medical cases.

2. Methods

Our approach uses text mining for disclosing the main themes of neurology case reports. The present study included five phases: data collection, disease and syndrome extraction, frequency analysis, relationship detection and analysis, and trend exploration (Fig. 1).

2.1. Data collection

Data collection in this research was carried out in two steps. In the first step, we retrieved a list of top 200 neurology journals based on impact factor indicator from the Scimago Journal & Country Rank website[2] in April 2018. In the second step, we retrieved the case reports based on the journal name indexed in the PubMed website. For example, we used *"case reports [Publication Type] AND lancet neurol[Journal]"* query to retrieved case reports in *The Lancet Neurology*. Of the 200 top neurology journals, we focused on 66 journals that published at least 50 case reports, defining them as the highly active journals for publishing case reports (Appendix A). The collected data is available at https://github.com/amir-karami/MedicalCaseReport-Diseases.

2.2. Disease and syndrome extraction

In this step, we used PubTator[3] developed by the National Center for Biotechnology Information (NCBI) to extract and annotate the collected case reports [16]. The PubTator service can annotate diseases, species, chemicals, genes, and mutations in the PubMed documents [17]. Fig. 2 shows an example of entity detection using PubTator including title, abstract, gene, chemical, disease, and mutation. This case describes a patient having breast cancer along with gene, chemical, and mutation information. For this study, we considered the disease entity that covers both disease and syndrome (DS).

2.3. Frequency analysis

Frequency analysis provides overall information about the detected DsSs [18]. Exploring high-frequency DsSs with bar chart and word cloud is a starting point for content analysis. Word cloud analysis visually summarizes text analysis and provides an overall view of the data in a corpus. This method presents the frequency of words in a corpus where the word size is proportional to the frequency of the word within the corpus- the larger size, the higher frequency. This approach has been used for a variety of applications, such as opinion mining [19]. Using word clouds to explore high-frequency DsSc reveals the important DsSc in the case reports over the past decades.

2.4. Relationship detection and analysis

Next, we turned our attention to detect relationships between DsSs. The goal of this analysis was to find DsSs that were discussed together in multiple case reports. There are two major approaches in content analysis for detecting the relationships between words in a corpus: co-occurrence analysis and the afore-mentioned topic modeling [20]. Previous studies have shown that topic modeling shows a better performance than co-occurrence analysis for large corpora [21]. Topic modeling has been applied on both short-length documents such as tweets and long-length documents like research papers [22,23]. Among different topic models, latent Dirichlet allocation (LDA) is the most popular topic model and also has demonstrated better performance than co-occurrence analysis with respect to word clustering [24,25]. According to the literature, LDA is a valid and widely used model with more than 25,000 citations in Google Scholar[4] for discovering categories of words in a corpus. LDA is a generative probabilistic model for categorizing the words that occur together in a corpus [26,27]. For

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[1] https://www.ncbi.nlm.nih.gov/pubmed?term=%22case%20reports%22%5BPublication%20Type%5D.

[2] https://www.scimagojr.com/journalrank.php?category=2728.

[3] https://www.ncbi.nlm.nih.gov/CBBresearch/Lu/Demo/PubTator/.

[4] https://scholar.google.com/scholar?cites=17756175773309118945&as_sdt=5,41&sciodt=0,41&hl=en.
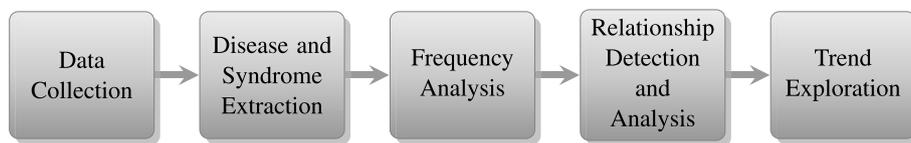
Fig. 1. Research framework.

29702197|t|Mutations in the estrogen receptor alpha hormone binding domain promote stem cell phenotype through notch activation in breast cancer cell lines.
29702197|a|The detection of recurrent mutations affecting the hormone binding domain (HBD) of estrogen receptor alpha (ERa/ESR1) in endocrine therapy-resistant and metastatic breast cancers has prompted interest in functional characterization of these genetic alterations. Here, we explored the role of HBD-ESR1 mutations in influencing the behavior of breast cancer stem cells (BCSCs), using various BC cell lines stably expressing wild-type or mutant (Y537 N, Y537S, D538G) ERa. Compared to WT-ERa clones, mutant cells showed increased CD44+/CD24- ratio, mRNA levels of stemness genes, Mammosphere Forming Efficiency (MFE), Self-Renewal and migratory capabilities. Mutant clones exhibited high expression of NOTCH receptors/ligands/target genes and blockade of NOTCH signaling reduced MFE and migratory potential. Mutant BCSC activity was dependent on ERa phosphorylation at serine 118, since its inhibition decreased MFE and NOTCH4 activation only in mutant cells. Collectively, we demonstrate that the expression of HBD-ESR1 mutations may drive BC cells to acquire stem cell traits through ER/NOTCH4 interplay. We propose the early detection of HBD-ESR1 mutations as a challenge in precision medicine strategy, suggesting the development of tailored-approaches (i.e. NOTCH inhibitors) to prevent disease development and metastatic spread in BC mutant-positive patients.
29702197   681   685   CD24   Gene   100133941
29702197   254   257   ERa   Gene   2099
29702197   258   262   ESR1   Gene   2099
29702197   442   446   ESR1   Gene   2099
29702197   613   616   ERa   Gene   2099
29702197   633   636   ERa   Gene   2099
29702197   991   994   ERa   Gene   2099
29702197   1161   1165   ESR1   Gene   2099
29702197   1290   1294   ESR1   Gene   2099
29702197   1234   1240   NOTCH4   Gene   4855
29702197   1014   1020   serine   Chemical   CHEBI:17822
29702197   310   324   breast   cancers   Disease   D001943
29702197   488   501   breast cancer   Disease   D001943
29702197   1501   1509   patients   Species   9606
29702197   599   604   Y537S   Mutation   p | SUB|Y|537|S

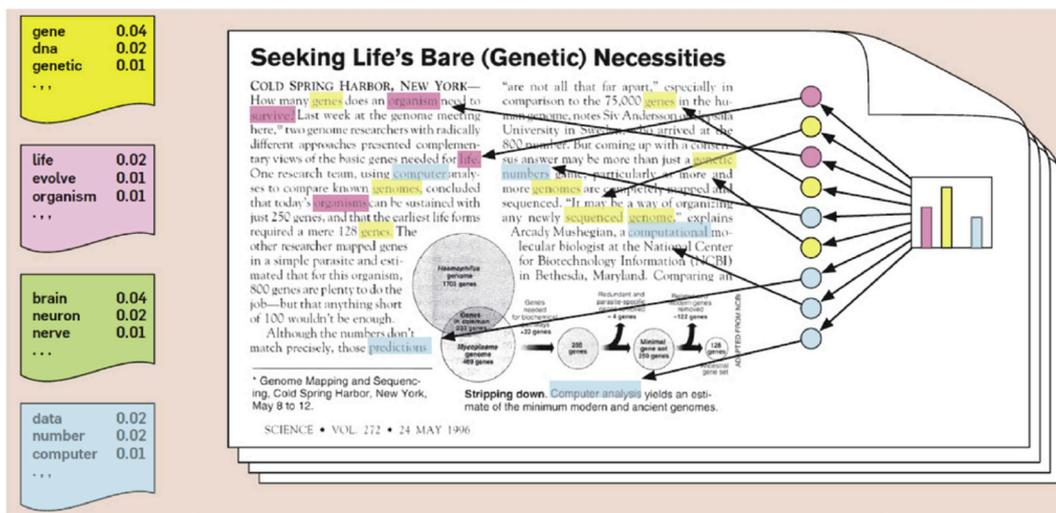**Fig. 2.** PubTator example.

Fig. 3. An example of LDA [42].

example in Fig. 3, LDA assigns "gene," "dna," and "genetic" into the same category.

LDA has been utilized for health applications such as diet, diabetes, exercise, and obesity [28–30], and LGBT health issues [31,32], and non-health applications such as business and organizations [33–35], spam detection [36], disaster management [37], and politics [38,39]. There are some work investigating related studies in medical and health domains using LDA such as exploring the literature of depressive disorders [17], biomedical literature [18,40], and adolescent substance use and depression [41].

To the best of our knowledge, this study is the first research uses LDA to analyze medical case reports. LDA assumes that there is an exchange between words and documents in a corpus [27]. In this research, we represent each case report (document) with the embedded DsSs (words) and don't consider other words such as title and abstract in the case report. Based on the LDA assumption, the neurology case reports are represented by categories of DsSs in our dataset. Another assumption of LDA is that a category, which is a group of related DsSs, has a different probability of occurrence for each of the case reports. This assumption can help to measure the weight of categories in each case report. In summary, LDA identifies the relationship between case reports and the categories, $P(Category|CaseReport)$, and categories and DsSs, $P(DS|Category)$.

For n case reports, m DsSs, and t categories, the outputs of LDA were: the probability of each of the DsSs per each category or $P(DS_i|C_k)$ and probability of each of the categories per each case report or $P(C_k|CR_j)$:

$$LDA \rightarrow \begin{bmatrix} P(DS_1|C_1) & \cdots & P(DS_1|C_t) \\ \vdots & \ddots & \vdots \\ P(DS_m|C_1) & \cdots & P(DS_m|C_t) \end{bmatrix} \& \begin{bmatrix} P(C_1|CR_1) & \cdots & P(C_1|CR_n) \\ \vdots & \ddots & \vdots \\ P(C_t|CR_1) & \cdots & P(C_t|CR_n) \end{bmatrix}$$

The top DsSs in each category, based on the order of $P(DS_i|C_k)$, were used to represent the categories. We also used $P(C_k|CR_j)$ to find the Significance of each Category, $SC(C_k)$. For an effective comparison between the categories, $SC(C_k)$ was normalized:

$$N\_SC(C_k) = \frac{\sum_{j=1}^{n} P(C_k|CR_j)}{\sum_{k=1}^{t} \sum_{j=1}^{n} P(C_k|CR_j)}$$

If $N\_SC(C_x) > N\_SC(C_y)$, it means that researchers discussed the diseases in category x more than the ones in category y. $N\_SC(C_k)$ can also help to find the weight of each category for each year and all the years.

2.5. Trend exploration

We explored the DsSs trends using a linear trend model across six decades. We used the frequency of DsSs and the categories of DsSs in the case reports within each year to detect and identify increasing and decreasing trends in research interest around the DsSs [17]. We used the *lm* function in R to measure $p-value$ and slope for each of the DsSs and categories. The $p-value$ determines whether a trend is significant and the slope shows whether a trend is increasing or decreasing. The trend shows increasing or decreasing importance of an entity. The slope shows the intensities of the trends, useful in comparing them.

3. Results

The data collection step has provided 65,525 case reports for 63 years, from 1955 to 2017, in the MEDLINE format. Fig. 4 shows the number of published neurology case reports per year over more than six
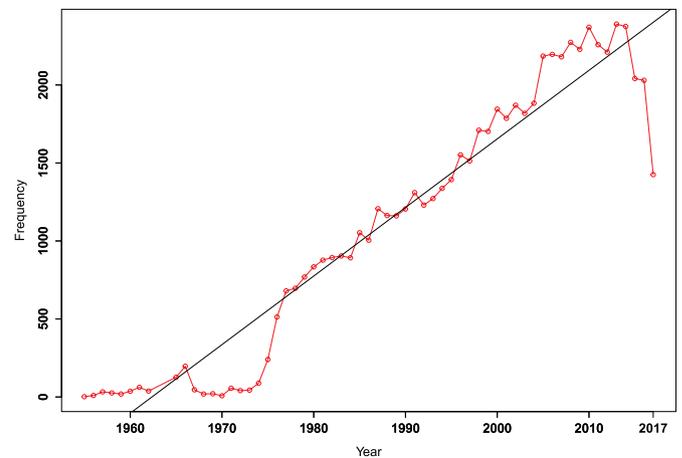

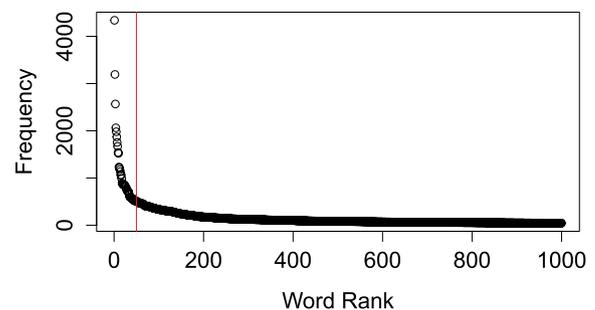**Fig. 4.** Frequency of case reports from 1955 to 2017.

Fig. 5. Frequency of DsSs. The vertical line shows the cut-off point for top-50 words in the word cloud.

decades along with the trend line. The linear trend was significant ($p < 0.05$) and had a positive value (43.95) for the slope indicating an increasing trend.

PubTator detected DsSs in 93% (61,149 out of 65,625) of the case reports. We found 258,487 DsSs among which 18,081 DsSs were unique. Word frequency analysis showed that 95% of DsSs occurred fewer than 50 times. With a median of 3 and an average of 14.3, the frequency of DsSs was between 2 (for 6,675 of the DsSs) and 4,319 (for tumor). Fig. 5 is in line with Zipf's law and illustrates the position of the top 50 words among the top 1000 high-frequency words. Zipf's law states that the frequency of a word in a corpus is inversely proportional to its frequency rank [43].

Figs. 6 and 7 illustrate the frequency of the top 10 high-frequency DsSs and the word cloud for the top 50 DsSs. These two figures indicate that tumor, seizures, and headache are the most frequent DsSs, characterizing 4339, 3190, and 2566 case reports, respectively. We didn't apply any stemming techniques in the identification of categories in case reports. For example, we didn't convert a plural form such as tumors to the singular one to distinguish the case reports studying multiple tumors from the ones investigating a single tumor.

Fig. 8 shows overall trends for the top 10 DsSs. Tumor was the most frequently mentioned DsS in the 1970s, 1980s, 2000s, and after 2010. However, seizures were the most frequent one in the 1990s. The frequency of headache was close to and in some years higher than the frequency of seizures after 2000.
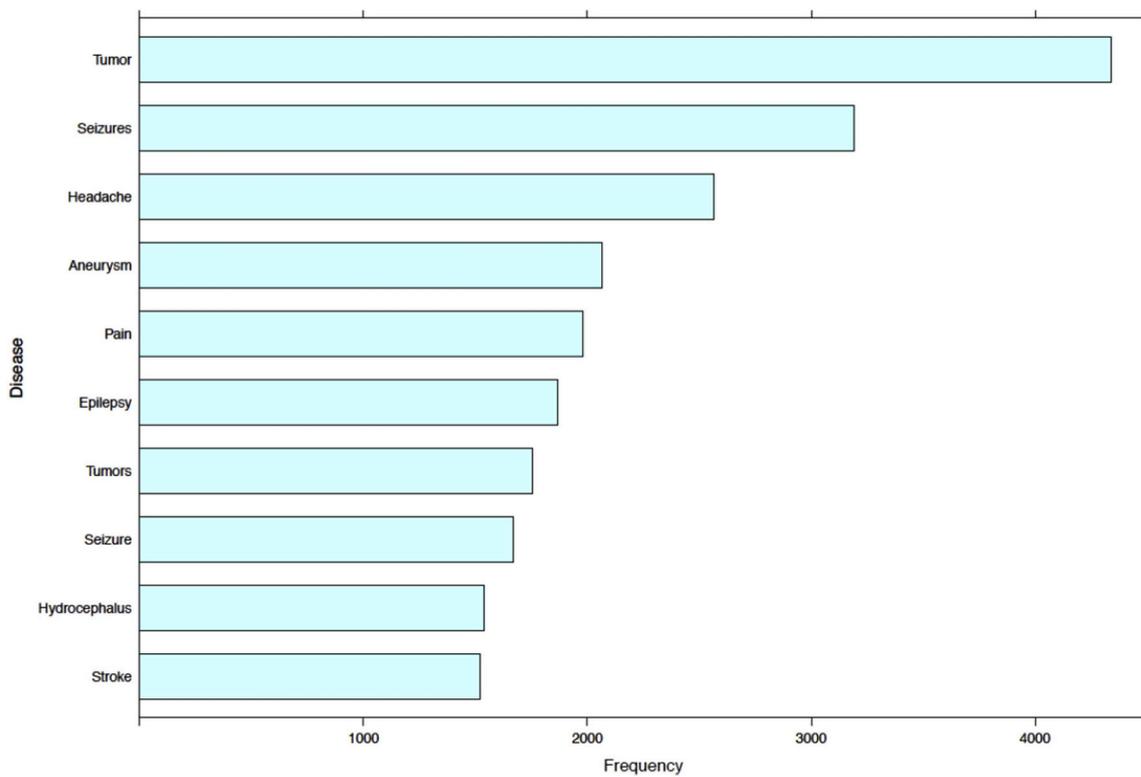
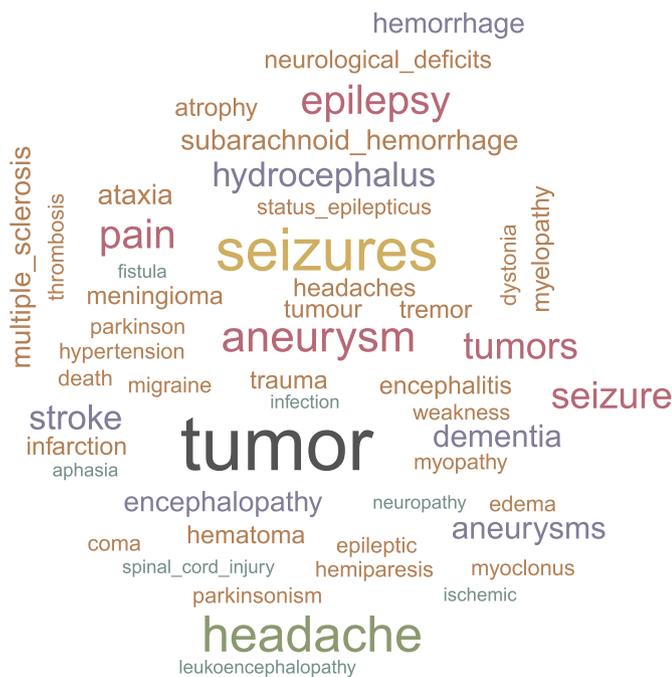**Fig. 6.** Frequency of the top 10 DsSs.
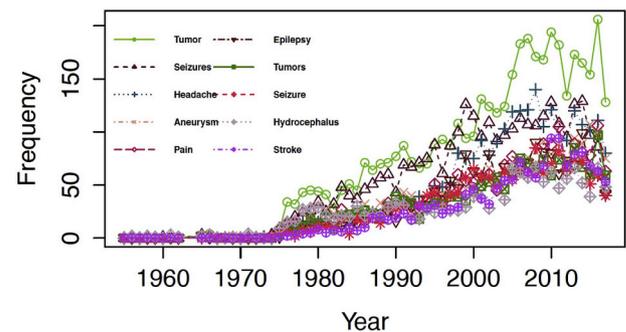

Fig. 7. Word cloud of the top 50 DsSs.

Fig. 8. Overall linear trends for the top10 DsSs.

and patterns for 9 out of 10 DsSs in the following years. The only exception was that the slope value of hydrocephalus was less than the slope value of stroke. This means that we would see more stroke-related case reports than hydrocephalus-related ones.

We found that 81% (50,944 out of 61,149) of case reports discussed multiple DsSs. This research used the Mallet implementation of LDA using Gibbs sampling with its default settings to categorize DsSs in the case reports with multiple DsSs.

To select an optimal number of categories, we applied a density-based method that assumes that the best performance of LDA is at the minimum average cosine distance of categories [45]. Applying the *ldatuning* R package[5] on the number of categories from 5 to 100 increased by 5 has shown the appropriate number of categories at 10. The Mallet implementation, which is a Java programming language for text mining purposes [44], was applied on the DsSs with 10 categories and

Fig. 9 and Table 1 illustrate the linear trend information of the top 10 DsSs from 1955 to 2017. The average number of studies per year for the top 10 DsSs was more than 25. The linear trend of the top 10 DsSs was significant ($p < 0.05$) with a positive slope indicating increasing trends. Based on the slope values, we expected to see the same ranking
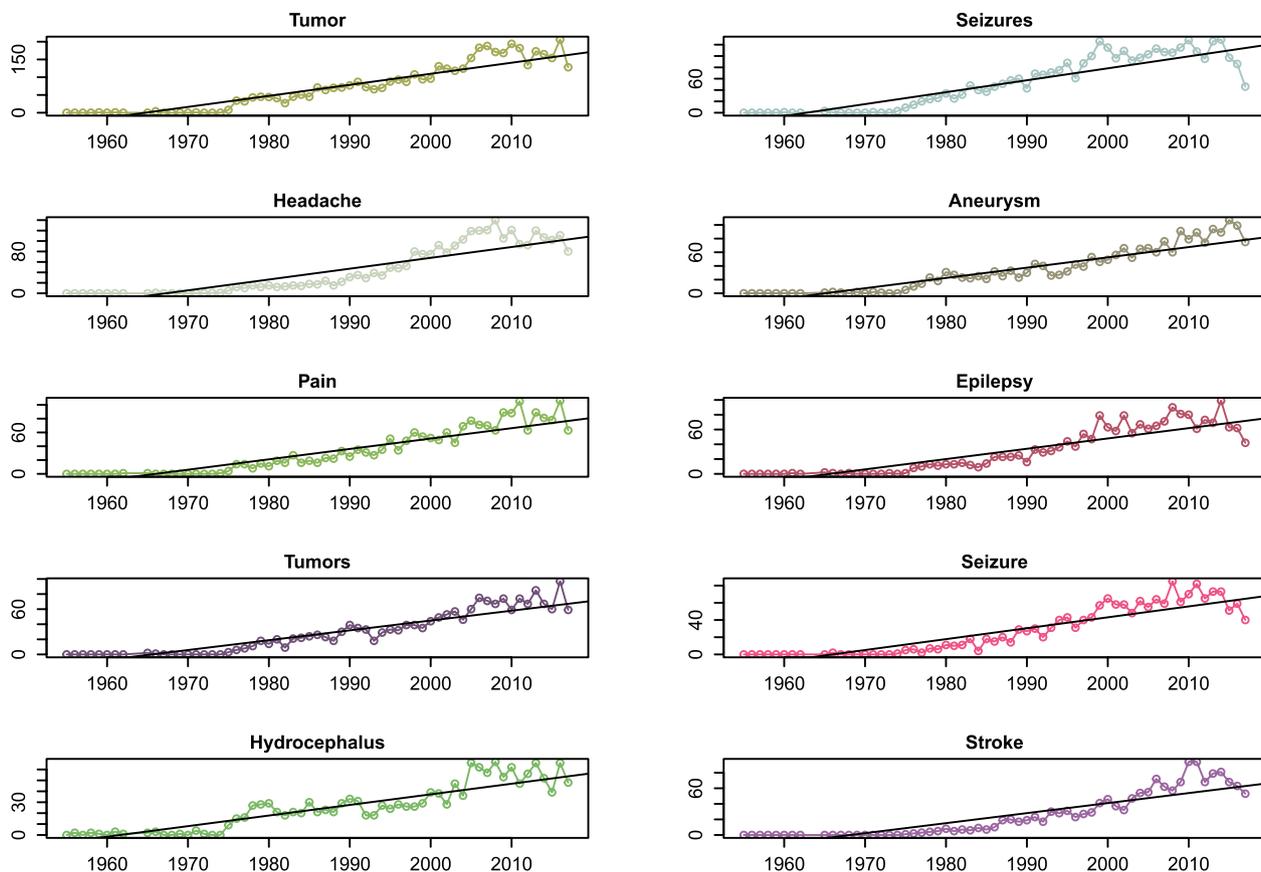

Fig. 9. Linear trends of the top 10 DsSs from 1955 to 2017.

Table 1
Linear trend data of top-10 DsSs from 1955 to 2017.

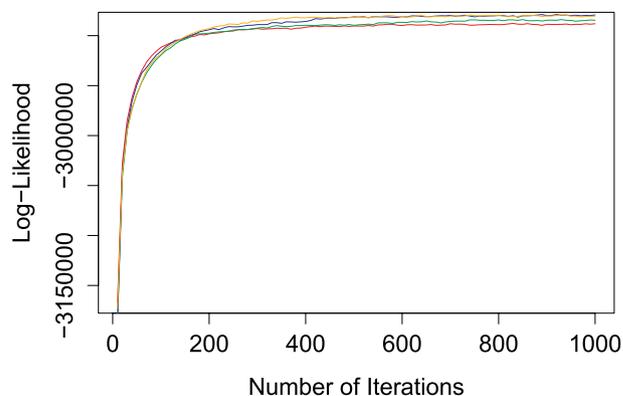| Disease	Frequency	Average/Year	Slope	P-Value
Tumor	4339	68.87	3.11	0.00
Seizures	3190	50.63	2.10	0.00
Headache	2566	40.73	2.07	0.00
Aneurysm	2066	32.79	1.50	0.00
Pain	1979	31.41	1.50	0.00
Epilepsy	1867	29.63	1.40	0.00
Tumors	1754	27.84	1.30	0.00
Seizure	1670	26.51	1.27	0.00
Hydrocephalus	1539	24.43	0.97	0.00
Stroke	1521	24.14	1.29	0.00

Fig. 10. Convergence of the log-likelihood for 5 sets of 1000 iterations.

1000 iterations.

Then, we evaluated the robustness of LDA on using the log-likelihood for five sets of 1000 iterations. LDA was trained on the case reports having multiple DsSs with 10 categories for five times and reached its maximum value after 500 iterations (Fig. 10). We compared the five sets using t-test and found that there isn't a significant difference ($p - value > 0.05$) between the five iterations with respect to

mean and standard deviation. This figure and the t-test show that there isn't a significant difference in log-likelihood convergence over different iterations.

Fig. 11 shows the distribution of categories over the case reports and each line represents a category. This figure indicates that the 10
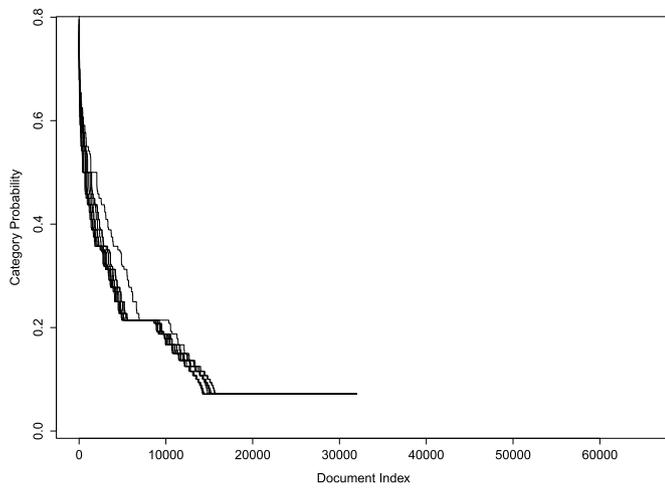
Fig. 11. Distribution of categories over the case reports with multiple DsSs.

categories have a high probability for less than 2000 case reports.

Table 2 shows the 10 categories. These categories show the possible relationships between the top 5 DsSs in each of the categories. We also explored the weight of categories and found that categories 3, 5, and 7 are the most discussed ones; however, the zero value of the standard deviation of the weights ranging from 0.09 to 0.11 shows no significant difference among the weights (Fig. 12). Therefore, we can assume that the categories have similar weight.

We investigated the yearly trends of categories for six decades from 1955 to 2017 (Fig. 13). The stream figure visualizes the evolution of categories based on the probability of the 10 categories in each of the years. Each color represents a category that horizontally flows from left to right. In Table 3 and Fig. 14, although $p - value$ <0.05 shows that the trends for categories 3, 8, and 10 are significant.

4. Discussion

Due to the lack of a macro level analysis and the high volume of

Table 2
Categories of relevant DsSs.

Category 1	Category 2	Category 3	Category 4	Category 5
headache	stroke	dementia	multiple_sclerosis	tremor
hydrocephalus	infarction	atrophy	encephalitis	dystonia
headaches	ischemic	ataxia	encephalopathy	parkinson
pain	hemiparesis	neuronal_loss	meningitis	parkinsonism
migraine	ischemic_stroke	gliosis	infection	depression

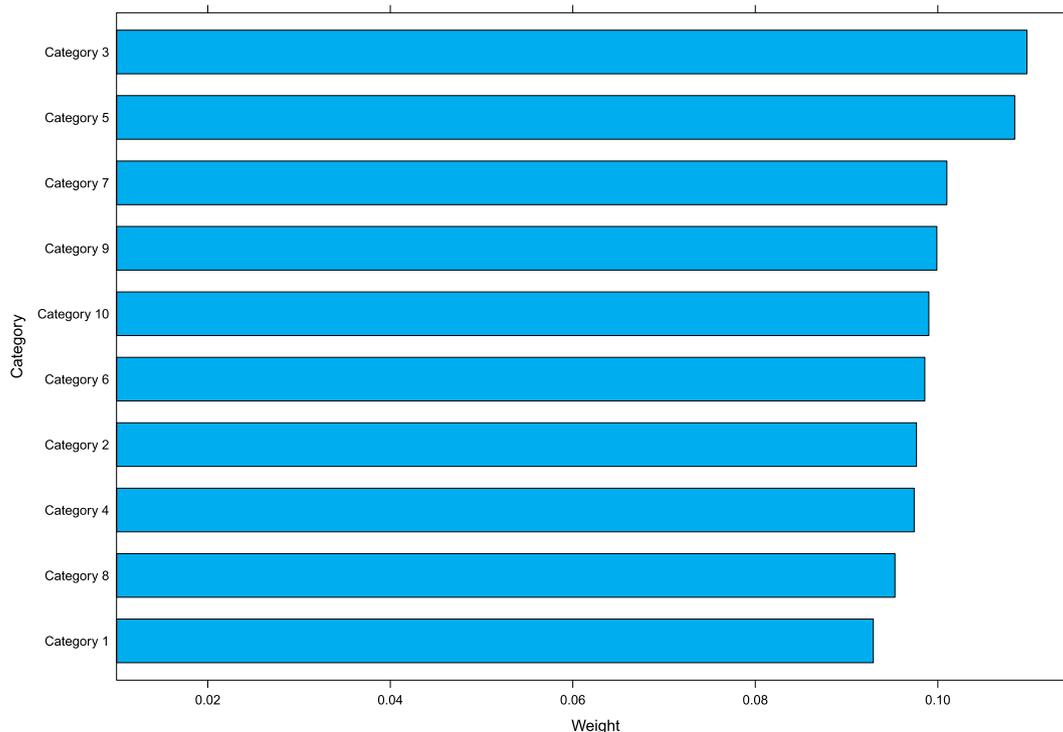| Category 6	Category 7	Category 8	Category 9	Category 10
tumor	weakness	pain	aneurysm	seizures
tumors	neuropathy	myelopathy	aneurysms	epilepsy
meningioma	myopathy	trauma	hemorrhage	seizure
tumour	polyneuropathy	spinal_cord_injury	subarachnoid_hemorrhage	epileptic
glioblastoma	peripheral_neuropathy	paraplegia	hematoma	status_epilepticus

Fig. 12. Weight of categories.
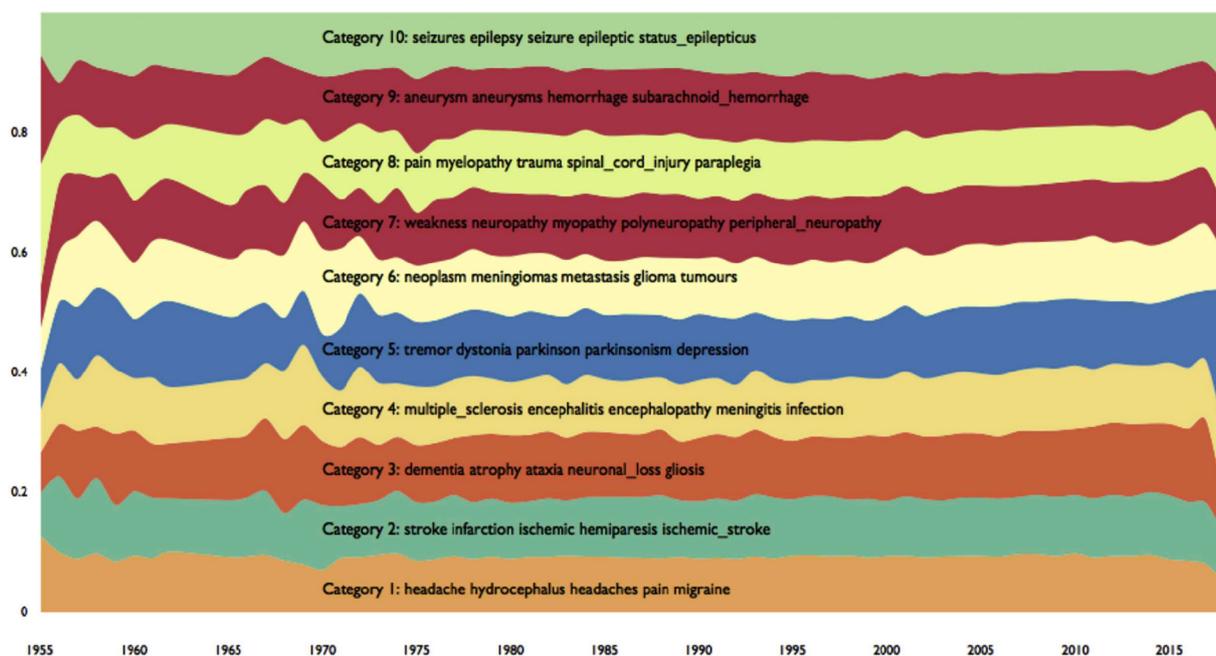
Fig. 13. Yearly stream graph of categories.

Table 3
Yearly linear trends of diseases.

Category	Weight	Slope	P-Value
Category 1	0.0929	−0.000109	0.071897
Category 2	0.0977	−0.000031	0.612404
Category 3	0.1098	0.000197	0.028806
Category 4	0.0974	0.000044	0.512252
Category 5	0.1084	0.000269	0.064952
Category 6	0. 0985	−0.000071	0.389706
Category 7	0.1009	0.000071	0.287937
Category 8	0.0953	−0.000295	0.010105
Category 9	0.0999	−0.000211	0.047734
Category 10	0.099	0.000137	0.023201

medical case reports, there is a need to utilize computational methods for the purpose of analyzing a large number of case reports. In this study we investigated DsSs in the neurology case reports to recognize patterns and provide additional insights using text mining. Analysis of case report entities such as DsSs provides a "bird's eye view" to understand the importance of the entities and their interactions.

Exploring the patterns of DsSs will provide vital insights into many aspects as follows. First, the high-frequency DsSs suggest their high importance to medical experts. Second, the DsSs in a category that have not been studied together can be considered as useful hypotheses for further investigation. Third, the detected trends show research streams. Fourth, sharp changes in the detected trends provide an overview of past studies and insights for future studies.

Through frequency analysis, we found high-frequency DsSs such as tumor(s), seizure(s), headache, aneurysm, pain, epilepsy, hydrocephalus, and stroke. This analysis shows the importance of these DsSs for researchers. Relationship detection and analysis generated 10 categories of DsSs. For example, the first category shows the case reports mentioning two or more of the represented DsSs, such as a paper

reporting headache, hydrocephalus, pain, and migraine [46]. Examples of other case reports for each of the categories can be found in Table 4.

The stream river figure has visualized how the ten categories have changed over more than 60 years. The width variation reflects the strength of the categories at each time slice. For example, the DsSs in category 1 were considered more in 1955 than 1970.

The World Health Organization (WHO) considers the detected DsSs in this study as the common neurological disorders.[6] This alignment between the WHO report and this study illustrates that researchers have allocated higher weight to the common DsSs in the case reports.

5. Conclusion

Medical experts have been contributing continuously to neurology case reports. Due to the rapid growth in the number of case reports and their overall large numbers, there is a need for a systematic analysis approach to help researchers, policymakers, and practitioners to have a large-scale understanding of the case reports. This study achieved this macro level analysis by applying text-mining and trend analysis methods on thousands of neurology case reports to detect and explore high frequency DsSs and their categories from 1955 to 2017.

The results show the ability of text mining methods to investigate DsSs in a large number of medical case reports and explore them for several decades to disclose interesting patterns. Our methodology demonstrates the usefulness of computational linguistics methods to study DsSs and their trends in medical case reports. The proposed approach can be used to provide a macro level analysis of medical literature by discovering interesting patterns and tracking them in specific time frames. The results illustrated the application of text mining for detecting DsSs and their relationships, and disclosing their trends in a large number of neurology case reports. We believe that this paper proposes a systematic approach for analysis of case reports in not only neurology but also other medical fields.

This study has some limitations. First, the collected case reports

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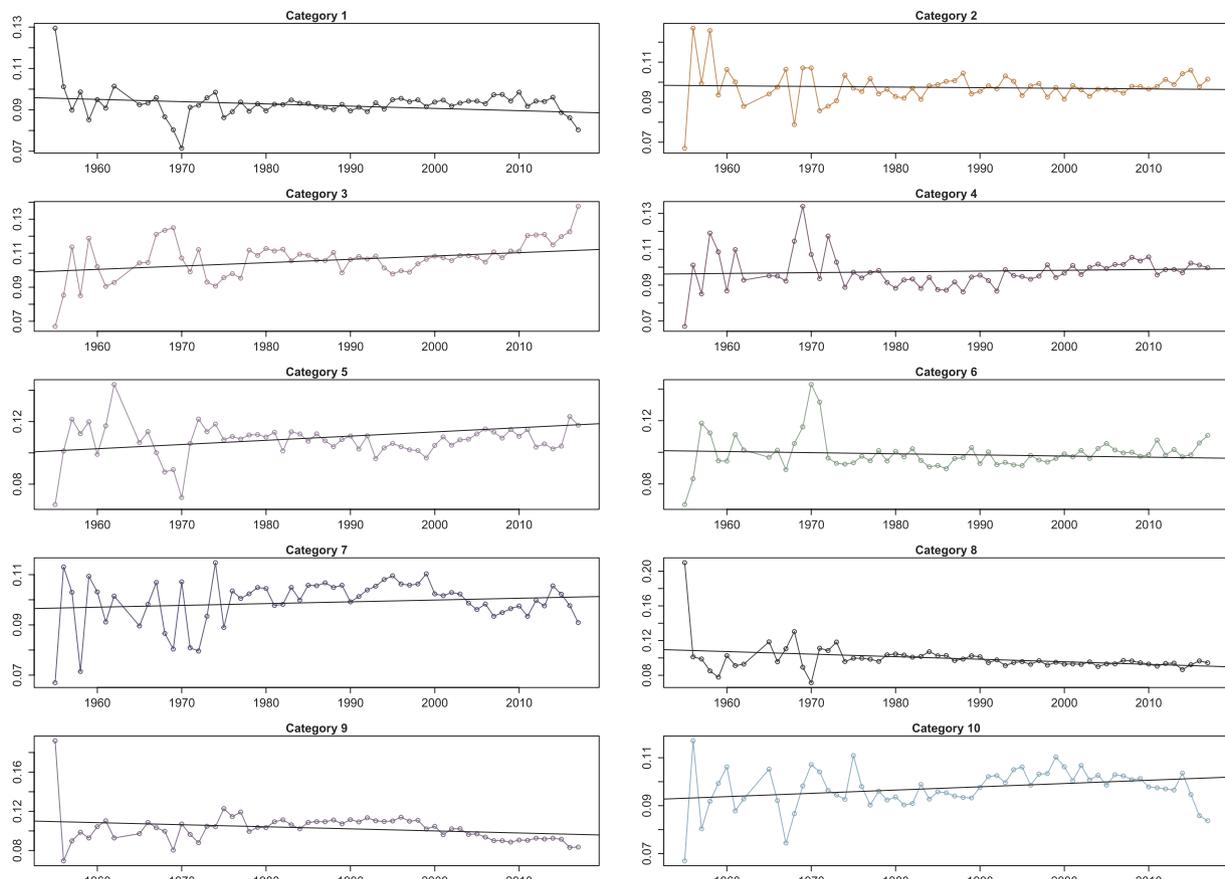[6] https://www.who.int/mental_health/neurology/neurodiso/en/.

Fig. 14. Yearly linear trends of DsSs.

Table 4
Case report examples for categories.

Category	Related Case Report	Reported Diseases and Syndromes
1	[46]	headache, hydrocephalus, pain, migraine
2	[47]	stroke, hemiparesis
3	[48]	ataxia, atrophy, neuron loss
4	[49]	meningitis, infection
5	[50]	tremor, dystonia, parkinson
6	[51]	tumor, meningioma
7	[52]	weakness, myopathy
8	[53]	myelopathy, spinal cord injury
9	[54]	aneurysm, hemorrhage
10	[55]	epilepsy, seizure

were only from the journals among the top 200 neurology journals in the Scimago Journal & Country Rank website. In our future work, we plan to incorporate additional neurology case reports, investigate other medical research areas, and compare them. Second, we only analyzed DsSs; however, there are other entities in the case reports. Therefore, we will investigate DsSs along with chemicals, mutations, genes, and species based on time and location variables.

Conflicts of interest

The authors state that they have no conflict of interest.

Acknowledgement

Appendix A. List of Journals

Acta neurochirurgica	Journal of neuropathology and experimental neurology
Acta neurologica Scandinavica	Journal of neurosurgery
Acta neuropathologica	Journal of neurosurgery. Pediatrics
Annals of neurology	Journal of neurosurgery. Spine
Behavioural neurology	Journal of neurosurgical anesthesiology
BMC neurology	Journal of neurovirology
Brain: a journal of neurology	Journal of the neurological sciences
Brain injury	Metabolic brain disease
Brain research	Multiple sclerosis and related disorders
Brain stimulation	Neurocritical care
Case reports in neurology	Neurologic clinics

Cephalalgia: an international journal of headache	Neurology
Cerebellum	Neuromodulation: journal of the International Neuromodulation Society
Clinical neurology and neurosurgery	Neuropathology: official journal of the Japanese Society of Neuropathology
Clinical neuropharmacology	Neuropathology and applied neurobiology
CNS spectrums	Neurophysiologie clinique = Clinical neurophysiology
Developmental medicine and child neurology	Neuroradiology
Epilepsia	NeuroRehabilitation
Epilepsy research	Neurorehabilitation and neural repair
European neurology	Neurosurgery
Headache	Neurosurgery clinics of North America
JAMA neurology	Neurosurgical focus
Journal of child neurology	Neurosurgical review
Journal of clinical and experimental neuropsychology	Pediatric neurology
Journal of clinical neurophysiology	Psychiatry and clinical neurosciences
Journal of clinical neuroscience	Seminars in neurology
Journal of geriatric psychiatry and neurology	Seminars in pediatric neurology
Journal of neuro-oncology	Spinal cord
Journal of neuro-ophthalmology	Stereotactic and functional neurosurgery
Journal of neuroimmunology	The journal of spinal cord medicine
Journal of neurointerventional surgery	The Lancet. Neurology
Journal of neurology	Topics in stroke rehabilitation
Journal of neurology, neurosurgery, and psychiatry	World neurosurgery

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