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Global research on artificial intelligence-enhanced human electroencephalogram analysis

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Abstract

The application of artificial intelligence (AI) technologies in assisting human electroencephalogram (EEG) analysis has become an active scientific field. This study aims to present a comprehensive review of the research field of AI-enhanced human EEG analysis. Using bibliometrics and topic modeling, research articles concerning AI-enhanced human EEG analysis collected from the Web of Science database during the period 2009–2018 were analyzed. After examining 2053 research articles published around the world, it was found that the annual number of articles had significantly grown from 78 to 468, with the USA and China being the most influential and prolific. The results of the keyword analysis showed that "electroencephalogram," "brain–computer interface," "classification," "support vector machine," "electroencephalography," and "signal" were the most frequently used. The results of topic modeling and evolution analyses highlighted several important issues, including *epileptic seizure detection*, *brain–machine interface*, *EEG classification*, *mental disorders*, *emotion*, and *alcoholism and anesthesia*. The findings suggest that such visualization and analysis of the research articles could provide a comprehensive overview of the field for communities of practice and inquiry worldwide.

Keywords Artificial intelligence technologies · Human brain · Electroencephalogram · Bibliometrics · Research topics · Visualization

1 Introduction

As a branch of computer science, artificial intelligence (AI) has had a long and continuous association with neuroscience. In AI, machines mimic human-associated "cognitive" functions, such as "learning" and "problem-solving" [1]. According to the computational theory of mind, the human mind or brain processes information much like how computers process information.

Technological advances in AI are frequently inspired and driven by the study and simulation of neuronal functions and neural computation, as well as neuroscience, with a focus on the design and implementation of highly intelligent machines that utilize information principles from the human brain [2–4]. For example, an artificial neural network (ANN), a specific AI technology, is inspired by brain architecture. Research of the human brain provides excellent opportunities and potential for developing novel AI technologies. At the same time, AI has an enormous repertoire of technologies that are key to various topics in computational brain science and which are able to significantly stimulate and inspire brain research progress. For

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example, magnetic resonance imaging (MRI) analysis, as a popular technique in brain diagnosis [5], has been proven to be significantly enhanced by AI technologies [6].

In the era of information and technological innovation, much AI research is inevitably related to neuroscience and psychology, with academic collaborations between these disciplines providing a significant amount of research output (e.g., [7–11]). Electrophysiological signals are commonly adopted to assess brain condition. Thus, electroencephalogram (EEG) signals contain rich information concerning brain electrical characteristics and are broadly adopted in different neuroscience studies and clinical practices, for example, the adoption of EEGs to diagnose, monitor, and manage neurological disorders [12]. Additionally, it is also capable of expressing human awareness and indicating depth of anesthesia [13].

Literature reviews have long been considered an essential and effective way to evaluate problems and solutions in specific research domains (e.g., [14–16]). Several scholars have carried out reviews on relevant topics (e.g., neuroscience-inspired AI), describing the development status of the research field. By integrating studies of AI and brain theory, Arbib [17] pointed out the emergence of increasingly common principles for AI and brain theory. Ullman [18] described a number of aspects of AI research that might help to understand certain brain functions in the area of visual perception. Martinez-Miranda and Aldea [19] presented a review of research about emotions in humans and AI from the 1980s to the 2000s. They first identified a list of emotions in human beings' performance and then reviewed research work into intelligent systems that integrate emotions. Hassabis et al. [11] surveyed the historical interactions between neuroscience and AI fields and demonstrated the progress of AI stimulated by human neural computation research. Lee et al. [20] briefly reviewed AI technologies in stroke imaging by discussing technical principles, potential clinical applications, and future roles. Using bibliometrics, Chen et al. [21] identified the status and trends of AI-driven human brain research from 2009 to 2018. Specifically, they analyzed the trends of annual articles and citations, identified productive publication sources and institutions, and visualized academic collaborations. Moreover, research topics were uncovered by the topic model. However, little is known about AI-enhanced human EEG analysis research. For example, what were the major research topics and their evolutions? Which countries/regions, institutions, and authors have contributed more to the field?

In order to fill the knowledge gap and facilitate research on AI-enhanced human EEG analysis, this paper uses bibliometric analysis combined with the word cloud technique and topic modeling analysis to produce a systematic review. By quantitively using mathematical and statistical methodologies, bibliometric analysis is a valuable tool for analyzing scientific studies and has been popularly implemented in a variety of disciplines and topics [22–28]. In particular, scholars have conducted bibliometric studies on the topic of neuroscience. For example, Kocak et al. [29] explored scientific publications concerning research in neuroscience by integrating algorithms and primary bibliometric analysis. The word cloud technique remains an effective content analysis method that has been increasingly applied to indicate the core research hotspots of a given topic [30, 31]. Topic models are considered to be flexible and effective in topic detection and tracking [32] within a large-scale textual dataset. A wide range of studies which apply topic models to various research fields (e.g., [33–35]) are available. These studies have proven that bibliometric analysis, the word cloud technique, and topic modeling are powerful tools to map academic literature.

There are four objectives in this study: first, to reveal the trends and features of the AI-enhanced human EEG analysis research during the period 2009–2018, second, to summarize the contributions of journals, countries/regions, and institutions around the world, as well as to explore the scientific relations between countries/regions and institutions, and third, to uncover prevalent research topics and see how they have evolved via keyword analysis and topic modeling analysis.

Our study contributes to the field of AI-enhanced human EEG analysis research in the following aspects: first, to provide a thorough overview of the status and trends concerning AI-enhanced human EEG analysis research, second, to enable scholars to recognize major sources publishing AI-enhanced human EEG analysis research, third, to assist scholars in identifying potential collaborators in relevant academic and technological activities, and fourth, to raise researchers' awareness of major topics requiring attention.

2 Data and methods

This study used a bibliometric technique to quantitatively evaluate academic output. The workflow of data collection and analyses can be seen in Fig. 1, including data retrieval, data filtering and screening, and data analyses.

We collected all English academic articles regarding AI-enhanced human brain research published during the period 2009–2018 in the Science Citation Index Expanded (SCI-EXPANDED) and Social Sciences Citation Index (SSCI) databases. A search using "TS" (Topics) was conducted on March 27, 2019. The retrieval terms were obtained following the procedure designed by Hassan et al. [36]. First, a list of seed keywords provided by domain experts was used to retrieve seed articles. Then, a new seed

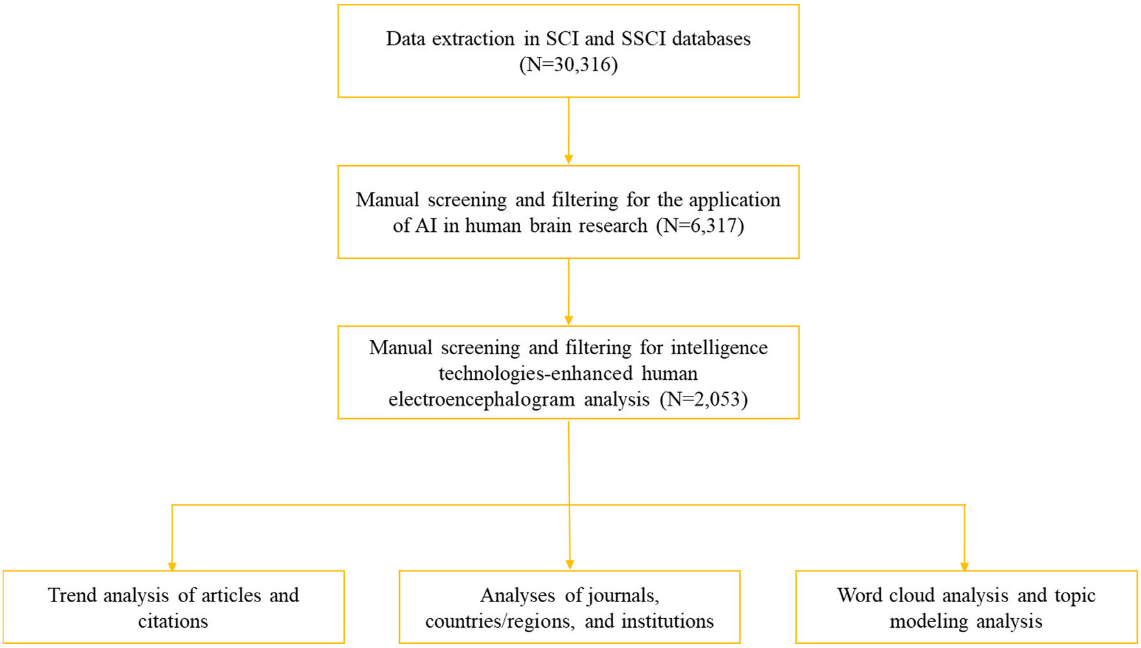

Fig. 1 Data collection and analyses workflow

keyword list was formed by collecting, processing, and integrating the keywords from the seed articles.

There were 30,316 research articles collected. Two domain experts filtered the articles to identify strictly relevant ones to both the human brain and AI [33]. These articles were further screened and filtered to ensure the application of EEGs by selecting those with terms "EEG" or "electroencephalogra*" (e.g., "electroencephalograph," "electroencephalogram," and "electroencephalographic") in title, abstract, or keywords in each article. In this manner, 2053 articles were selected. After identifying and extracting countries/regions and institutions from the author addresses, the contributions of various countries/regions and institutions could be computed. Research items from Hong Kong, Macau, and Taiwan were independently counted, whereas articles originating from England, Scotland, Northern Ireland, and Wales were grouped as the UK. The Hirsch index (H-index) was used to measure academic influence. It denotes that each H of an author's articles has no less than H citations [37]. The index is an integrated way of measuring both the quantity and quality of an author in terms of citations and is now commonly used to assess the scientific impact of journals, countries, or institutions [26].

Since the keywords of academic articles are normally applied to represent research topics, word cloud analysis based on keyword frequency was conducted using an R package called wordcloud2.[1] Word clouds are defined as visual representations of textual data [38], which adopt a variety of visual styles to arrange and depict significant words. Now a straightforward and popular technique for text visualization [39], it consists of four steps. First, prepare the input data with two columns for keywords and frequency specifications, respectively. Second, load the packages wordcloud2, Rwordseg,[2] and tmcn[3] using the library function. Third, visualize the word cloud using the wordcloud2 function and the input data. Lastly, adjust the size, color of the displayed keywords, and shape of the generated word cloud using specific parameters inside the function. In the cloud, the point size of the font indicates keyword frequency in relevant articles.

To ensure analysis efficiency and adequacy, keyword pre-processing was a necessary step. First, all keywords were extracted and converted to lowercase. Second, abbreviations were substituted with full names, for example, "PET" was replaced by "positron emission tomography," "MRI" was replaced by "magnetic resonance imaging," "BCI" was replaced by "brain-computer interface," "SVM" was replaced by "support vector machine," and "MEG" was replaced by "magnetoencephalography." Third, replicated keywords such as "human" and "humans" were unified. Finally, keywords such as "review," "study," and "article" were eliminated, since they did not convey actual information to the study. To explore the evolution of research topics, five periods of time were obtained: 2009–2010 (172 articles), 2011–2012 (219

[1] https://cran.r-project.org/web/packages/wordcloud2/vignettes/wordcloud.html.

[2] https://cran.r-project.org/web/packages/Rwordseg/index.html.

[3] https://cran.r-project.org/web/packages/tmcn/index.html.

articles), 2013–2014 (298 articles), 2015–2016 (534 articles), and 2017–2018 (830 articles).

In addition, to further enable a deep understanding of major issues and concerns among authors regarding AI-enhanced EEG analysis, we adopted a semi-automated machine learning technique called structural topic model (STM) [40, 41] to infer the latent dimensions inherent in the multitude of items of the 2053 articles. STM is an empirical method used to find the underlying topics of the field embedded within the textual content of the research articles concerning AI-enhanced EEG analysis. It organizes articles into "topics" based on content homogeneity concerning the individual topic. A clustering technique explores term co-occurrence across articles and allocates terms to different clusters. Based on the pre-defined number of topics, the probability indicating the distribution of an article to each topic is computed. Representative terms and articles for each topic are then identified.

STM was implemented using an R package stm [40]. Terms extracted from titles, abstracts, and keywords were selected and pre-processed. First, the terms were transformed into lowercase. Second, numbers, punctuation, and common stop terms such as "an," "a," and "in" were removed. Additionally, we followed the suggestion by Chen et al. [25] to allocate weights to terms extracted from different parts of an article.

To obtain insights into major issues of concern in research on AI-enhanced EEG analysis, we fitted 26 different models based on the numbers of topics, counting from 5 to 30. We then computed the semantic coherence and exclusivity for model selection [42, 43]. Semantic coherence is higher when more possible terms within one topic normally appear together, while exclusivity is higher when more terms are specifically tied to a topic. Figure 2 illustrates the average values of coherence and exclusivity for the 26 models. In the figure, each point represents a model with its name indicating how many topics are considered. For example, the point labeled "15-topic model" represents a model fitted with 15 topics. The figure indicates that 15- and 16-topic models achieve higher values for the two measures. Interpretations of the 15- (see Table S1 in Appendix) and 16-topic models are shown in Table 1. For the two models (i.e., with the numbers of topics being 15 and 16), our experts evaluated their interpretability and comparative efficacy based on the criteria proposed in [32] and found that an important topic labeled "neural network" was missed in the 15-topic model. Thus, the experts chose the 16-topic model as the best model.

3 Results

3.1 Trend analyses of articles and citations

Statistical computing was conducted on the numbers of articles and citations. Figure 3 shows the development trends of the numbers of articles and citations concerning AI-enhanced human EEG analysis. We also adopted polynomial regression analysis to model article and citation trends. The results showed a significantly increasing trend in the number of articles, reflecting a growing research interest in the application of AI technologies for human EEG analysis. This is also indicated by the estimated model of $y1 = 5.632576x^2 - 22{,}641.69x + 22{,}753{,}700$ (adjusted R-squared = 0.9843, p value: 1.992e-07). From the citation perspective, significant growth in the quantity was also revealed, with a regression model of $y2 = 93.29167x^2 - 374{,}830.8x + 376{,}502{,}500$ (adjusted R-squared = 0.9922, p value: 1.747e−08). Both the trends of articles and citations demonstrated a growing research interest in, and increasingly wide influence of, AI-enhanced human EEG analysis research.

In Fig. 3, we also present the top ten most impactful articles according to the number of annual citations (*C*/*Y*), calculated as total citations/(2018 + 1-publishing year) [24]. Of the ten articles, the most impactful was by Stam et al. [44], with a *C*/*Y* value of 46.60. Based on graph theory, this article explored changes in sizable resting-state brain networks in people with Alzheimer's disease. It is worth noting that four out of the ten most impactful articles were published in 2010, including [45–48]. The fifth most impactful article, with a *C*/*Y* value of 30, was by Acharya et al. [49], which presented an approach to automatically detect normal, pre-ictal, and ictal conditions from EEG signals. 2015 and 2017 witnessed the publication of two impactful AI-enhanced EEG studies. Specifically, studies [50, 51] were published in 2015, and studies [52, 53] were published in 2017. These top ten articles ranked by annual citations, as well as the top ten ranked by total citations, are listed in Table 2. Six articles are listed in the top ten across both types of ranks, including [44–49]. This indicates their wide impact on AI-enhanced EEG research.

3.2 Top journals

The selected 2053 articles were distributed across 416 journals, among which the top 16 based on the H-index are shown in Table 3. Together, these journals accounted for 38.09% of the selected articles. Such a distribution indicates a great diversity in journals and disciplines. *Expert Systems with Applications* had the highest H-index value (23), followed by *IEEE Transactions on Biomedical*

Fig. 2 Model diagnostics for STM (mean statistics were calculated for all topics of the corresponding model)

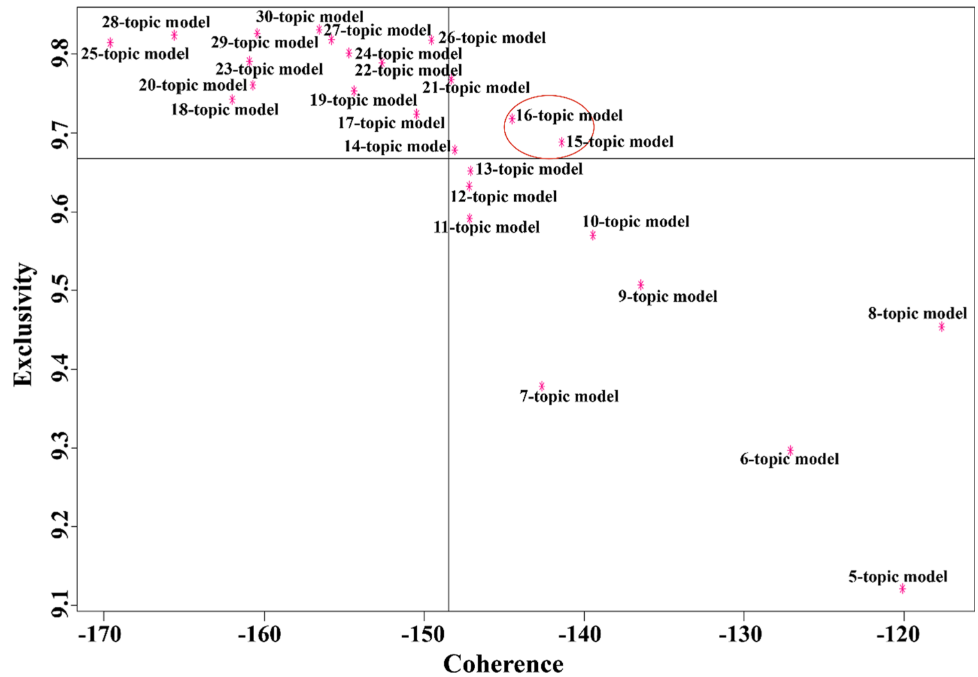

Table 1 Comparison of the 15- and 16-topic models

Labels for 15-topic model	Labels for 16-topic model
Brain–machine interface	*Brain–machine interface*
Epileptic seizure detection	*Epileptic seizure detection*
Fatigue driving	*Fatigue driving*
Depression	*Depression*
Cognitive control and performance	*Cognitive control and performance*
Alcoholism and anesthesia	*Alcoholism and anesthesia*
EEG spectral analysis	*EEG spectral analysis*
Emotion	*Emotion*
Sleep and sleep quality	*Sleep and sleep quality*
EEG artifact removal	*EEG artifact removal*
Signal and semantics	*Signal and semantics*
EEG classification	*EEG classification*
Epilepsy	*Epilepsy*
Mental disorders	*Mental disorders*
Vision	*Vision*
	Neural network

Engineering (21 H-index, 49 articles) and *Journal of Neuroscience Methods* (21 H-index, 51 articles). From a productivity perspective, among the 16 listed journals, *Journal of Neural Engineering* and *Biomedical Signal Processing and Control* were found to be the most prolific, each with 75 articles. However, their H-index values were relatively lower compared with the most influential ones. Comparing the number of articles published in different periods, some journals focused more on AI-enhanced human EEG analysis research and showed an increase in rank, e.g., *Biomedical Signal Processing and Control* and *Journal of Neural Engineering*. On the other hand, some journals tended to be less concerned about AI-enhanced human EEG analysis research and showed a decrease in rank, e.g., *Expert Systems with Applications* and *IEEE Transactions on Biomedical Engineering*.

3.3 Distribution of articles by country/region

In total, 74 countries/regions were identified from the 2053 research articles concerning AI-enhanced human EEG analysis from 2009 to 2018. Table 4 lists the top 14

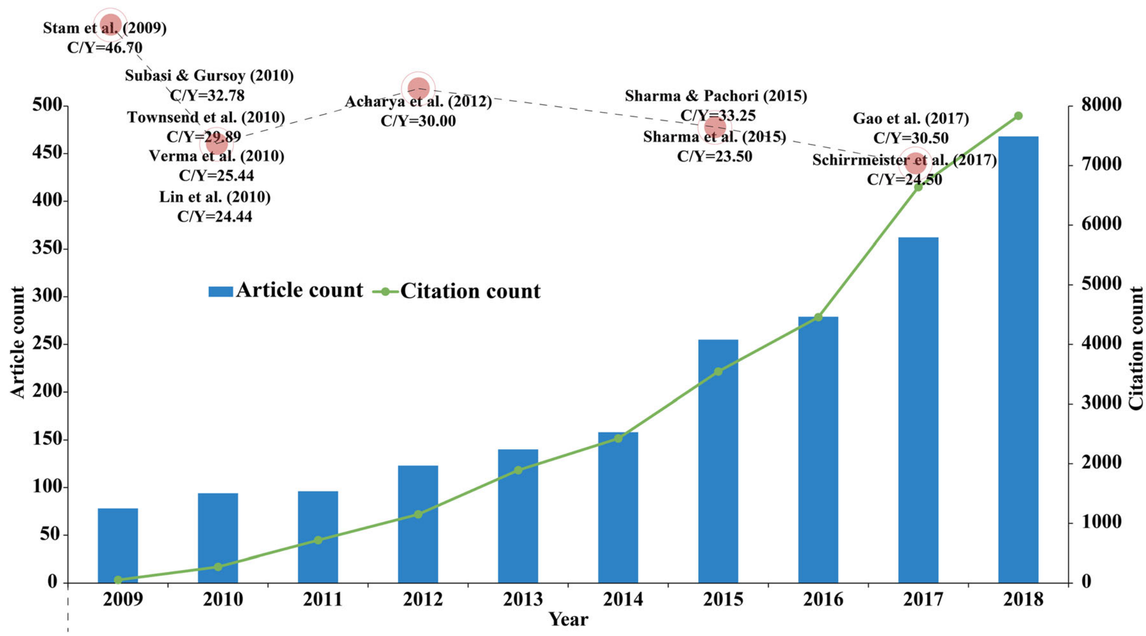

Fig. 3 Trend analyses of articles and citations

countries/regions based on the H-index. Of the 2053 articles, the USA contributed 416 articles, accounting for 20.26%, followed by China (18.66%), India (9.60%), and the UK (7.80%). Based on the H-index, the USA (41), China (32), India (26), Singapore (26), and Germany (25) were the top five. Comparing the article count of different periods, some countries/regions tended to focus more on AI-enhanced human EEG analysis research and showed an increase in rank, e.g., India and Australia. On the other hand, some countries/regions tended to be less concerned about AI-enhanced human EEG analysis research and showed a decrease in rank, e.g., Singapore and Netherlands.

3.4 Distribution of articles by institution

A total of 1800 institutions participated in the publication of the 2053 research articles concerning AI-enhanced human EEG analysis from 2009 to 2018. The top 13 institutions based on the H-index are displayed in Table 5. Among them, two originated from India, two from the Netherlands, two from Singapore, and two from the USA. Based on the H-index, *Indian Institute of Technology* was ranked number one with an H-index of 21, the highest number of citations (1549), and the most articles (62). Other influential institutions included *Ngee Ann Polytechnic* (H-index of 19), *Nanyang Technological University* (13), *The Ohio State University* (13), and *University of Malaya* (13). Comparing the articles published across the different periods, some institutions tended to focus more on AI-enhanced human EEG analysis research and showed an increase in rank, e.g., *University of Malaya* and *Indian Institute of Information Technology*. On the other hand, some institutions tended to be less concerned about AI-enhanced human EEG analysis research and showed a decrease in rank, e.g., *The Ohio State University* and *Aristotle University of Thessaloniki*.

3.5 Analyses of scientific collaborations

The number of scientific collaborations (from 5 to 50) between countries/regions is illustrated in Fig. 4. The node size denotes the article count of each country/region. The formation of different groups according to continent information can be observed via the different colors. In general, it is noted that countries/regions from the same continent tend to show closer collaborations in research on AI-enhanced EEG analysis. Each of the sub-figures depicts the number of collaborative relationships between countries/regions. For brevity, we only provide descriptions for Fig. 4a, n. Specifically, Fig. 4a shows the number of collaborative relationships among countries/regions that totaled five. Most of the countries/regions are from Europe, with close collaborations among these countries/regions being apparent. Figure 4n shows the collaborative relationships among countries/regions with a minimum of 20 collaborations. The USA and China collaborated the most (50 articles), while other close collaborators included Singapore and India (29), the USA and Germany (25), Singapore and Malaysia (23), and Malaysia and India (21). The collaborative cluster formed by Malaysia, Singapore, and India is worth noting. In short, the close collaborations

Table 2 Top articles ranked by number of annual citations and total citations

References	Title	Year	*C/Y*
Top articles ranked by number of annual citations (C/Y)			
Stam et al. [44]	Graph theoretical analysis of magnetoencephalographic functional connectivity in Alzheimer's disease	2009	46.70
Sharma and Pachori [50]	Classification of epileptic seizures in EEG signals based on phase space representation of intrinsic mode functions	2015	33.25
Subasi and Gursoy [45]	EEG signal classification using PCA, ICA, LDA, and support vector machines	2010	32.78
Gao et al. [52]	Visibility graph from adaptive optimal kernel time–frequency representation for classification of epileptiform EEG	2017	30.50
Acharya et al. [49]	Automated diagnosis of epileptic EEG using entropies	2012	30.00
Townsend et al. [46]	A novel P300-based brain–computer interface stimulus presentation paradigm: Moving beyond rows and columns	2010	29.89
Verma et al. [47]	A micro-power EEG acquisition SoC with integrated feature extraction processor for a chronic seizure detection system	2010	25.44
Schirrmeister et al. [53]	Deep learning with convolutional neural networks for EEG decoding and visualization	2017	24.50
Lin et al. [48]	EEG-based emotion recognition in music listening	2010	24.44
Sharma et al. [51]	Application of entropy measures on intrinsic mode functions for the automated identification of focal electroencephalogram signals	2015	23.50
References	**Title**	**Year**	**TC**
Top articles ranked by total citations (TC)			
Stam et al. [44]	Graph theoretical analysis of magnetoencephalographic functional connectivity in Alzheimer's disease	2009	467
Subasi and Gursoy [45]	EEG signal classification using PCA, ICA, LDA, and support vector machines	2010	295
Townsend et al. [46]	A novel P300-based brain–computer interface stimulus presentation paradigm: Moving beyond rows and columns	2010	269
Verma et al. [47]	A micro-power EEG acquisition SoC with integrated feature extraction processor for a chronic seizure detection system	2010	229
Tzallas et al. [54]	Epileptic seizure detection in EEGs using time–frequency analysis	2009	228
Lin et al. [48]	EEG-based emotion recognition in music listening	2010	220
Acharya et al. [49]	Automated diagnosis of epileptic EEG using entropies	2012	210
Orhan et al. [55]	EEG signals classification using the *K*-means clustering and a multilayer perceptron neural network model	2011	168
Rivet et al. [56]	xDAWN algorithm to enhance evoked potentials: Application to brain–computer interface	2009	168
Petrantonakis and Hadjileontiadis [57]	Emotion recognition from EEG using higher order crossings	2010	163

among countries/regions indicates that international collaboration in this research field is quite common.

Figure 5 shows the number of scientific collaborative relationships among institutions ranging from 5 to 19. Node size represents the article count for each institution. The colors of the groups represent the countries/regions of the institutions. In general, it is noted that institutions from the same countries/regions collaborated more in research on AI-enhanced EEG analysis. Each of the sub-figures shows the number of collaborative relationships between institutions. Specifically, Fig. 5a shows the number of collaborative relationships among institutions that totaled five. A total of 35 institutions were found, with five being from Iran, five from the USA, four from Malaysia, three from Singapore, and three from Taiwan. There were four partners that had each collaborated in six articles, as shown in Fig. 5b, including *University of Chinese Academy of Sciences* and *Chinese Academy of Sciences*, *Istituto di Ricovero e Cura a Carattere Scientifico* and *University of Tubingen*, *King Saud University* and *Universiti Teknologi Petronas*, and *Nanyang Technological University* and *Ngee Ann Polytechnic*. Figure 5c shows four partners with the number of collaborations totaling seven, including *Singapore University of Social Sciences* and *Ngee Ann*

Table 3 Top journals ranked by H-index

Journal	2009–2018			2009–2013		2014–2018	
	H	A (R)	C (R)	A (R)	C (R)	A (R)	C (R)
Expert Systems with Applications	23	60 (5)	1725 (2)	28 (1)	271 (3)	32 (9)	1454 (2)
IEEE Transactions on Biomedical Engineering	21	49 (10)	1802 (1)	25 (2)	297 (2)	24 (17)	1505 (1)
Journal of Neuroscience Methods	21	51 (7)	1342 (3)	22 (4)	253 (4)	29 (11)	1089 (3)
International Journal of Neural Systems	19	40 (13)	1053 (6)	13 (9)	159 (6)	27 (13)	894 (7)
Neurocomputing	19	50 (9)	1038 (8)	17 (6)	94 (11)	33 (8)	944 (5)
Biomedical Signal Processing and Control	18	75 (1)	1116 (5)	12 (10)	83 (12)	63 (1)	1033 (4)
IEEE Transactions on Neural Systems and Rehabilitation Engineering	18	53 (6)	899 (11)	11 (13)	129 (9)	42 (6)	770 (11)
Neuroimage	18	65 (3)	928 (9)	18 (5)	137 (7)	47 (3)	791 (10)
PLoS ONE	17	64 (4)	849 (12)	17 (6)	116 (10)	47 (3)	733 (12)
Journal of Neural Engineering	17	75 (1)	907 (10)	16 (8)	65 (16)	59 (2)	842 (9)
Clinical Neurophysiology	15	51 (7)	1161 (4)	23 (3)	304 (1)	28 (12)	857 (8)
Computer Methods and Programs in Biomedicine	14	28 (18)	570 (13)	7 (17)	37 (27)	21 (18)	533 (13)
Frontiers in Neuroscience	13	44 (12)	527 (15)	10 (14)	28 (35)	34 (7)	499 (14)
Computers in Biology and Medicine	12	31 (15)	417 (16)	12 (10)	52 (21)	19 (20)	365 (15)
Clinical EEG and Neuroscience	10	23 (21)	307 (19)	10 (14)	79 (13)	13 (27)	228 (24)
Journal of Medical Systems	10	23 (21)	311 (18)	12 (10)	55 (19)	11 (30)	256 (20)

R ranking position, *H* H-index, *A* article count, *C* citation count

Table 4 Top countries/regions ranked by H-index

Country/region	2009–2018			2009–2013		2014–2018	
	H	A (R)	C (R)	A (R)	C (R)	A (R)	C (R)
USA	41	416 (1)	7153 (1)	127 (1)	1196 (1)	289 (2)	5957 (1)
China	32	383 (2)	3633 (9)	52 (2)	223 (9)	331 (1)	3410 (2)
India	26	197 (3)	2746 (15)	24 (9)	148 (15)	173 (3)	2598 (3)
Singapore	26	74 (15)	2313 (4)	28 (7)	406 (4)	46 (16)	1907 (6)
Germany	25	143 (5)	2357 (6)	37 (5)	279 (6)	106 (5)	2078 (4)
UK	24	160 (4)	2379 (3)	42 (3)	432 (3)	118 (4)	1947 (5)
Netherlands	19	73 (16)	1829 (2)	29 (6)	512 (2)	44 (17)	1317 (7)
Iran	19	106 (7)	1441 (5)	41 (4)	293 (5)	65 (9)	1148 (9)
Turkey	18	75 (14)	1475 (7)	24 (9)	239 (7)	51 (14)	1236 (8)
Japan	18	79 (10)	1115 (10)	16 (16)	207 (10)	63 (10)	908 (14)
Canada	18	92 (8)	1204 (8)	22 (13)	228 (8)	70 (7)	976 (13)
Spain	18	79 (10)	1179 (14)	23 (11)	149 (14)	56 (12)	1030 (10)
South Korea	18	85 (9)	1106 (20)	25 (8)	117 (20)	60 (11)	989 (11)
Australia	18	107 (6)	1111 (18)	17 (15)	128 (18)	90 (6)	983 (12)

R ranking position, *H* H-index, *A* article count, *C* citation count

Polytechnic, *Singapore Management University* and *Indian Institute of Technology*, *Swiss Federal Institute of Technology* and *University of Zurich*, and *National Institute of Technology and Ngee Ann Polytechnic*. There were two partners that had each collaborated in nine articles, as shown in Fig. 5d, including *University of Tehran* and *Islamic Azad University*, and *University of Malaya* and *Indian Institute of Technology*. Figure 5e shows two partners with the number of collaborations totaling ten, including *Indian Institutes of Information Technology* and *Indian Institute of Technology*, and *Singapore Management University* and *University of Malaya*. There were two partners that had each collaborated in 11 articles, as shown in Fig. 5f, including *Ngee Ann Polytechnic* and *Indian Institute of Technology*, and *Singapore Management University* and *Ngee Ann Polytechnic*. Figure 5g shows

Table 5 Top institutions ranked by H-index

Institution	Country/region	2009–2018			2009–2013		2014–2018	
		H	A (R)	C (R)	A (R)	C (R)	A (R)	C (R)
Indian Institute of Technology	India	21	62 (1)	1549 (1)	10 (3)	40 (60)	52 (1)	1509 (1)
Ngee Ann Polytechnic	Singapore	19	37 (2)	1320 (2)	12 (1)	235 (3)	25 (3)	1085 (2)
Nanyang Technological University	Singapore	13	23 (6)	868 (5)	10 (3)	160 (9)	13 (23)	708 (4)
The Ohio State University	USA	13	17 (22)	936 (4)	8 (9)	191 (6)	9 (51)	745 (3)
University of Malaya	Malaysia	13	31 (3)	662 (7)	4 (28)	42 (51)	27 (2)	620 (6)
Graz University of Technology	Austria	12	15 (34)	426 (16)	5 (19)	103 (13)	10 (42)	323 (19)
Vrije Universiteit Amsterdam	Netherlands	12	18 (17)	1058 (3)	9 (6)	357 (1)	9 (51)	701 (5)
University of California, San Diego	USA	11	25 (5)	583 (10)	5 (19)	44 (46)	20 (8)	539 (7)
University of Tubingen	Germany	11	22 (10)	325 (31)	6 (10)	18 (156)	16 (13)	307 (23)
Aristotle University of Thessaloniki	Greece	10	17 (22)	556 (11)	9 (6)	62 (24)	8 (60)	494 (8)
Indian Institutes of Information Technology	India	10	23 (6)	400 (19)	2 (109)	9 (240)	21 (5)	391 (13)
Radboud University Nijmegen	Netherlands	10	20 (13)	760 (6)	10 (3)	277 (2)	10 (42)	483 (9)
Institute of Physical and Chemical Research	Japan	10	18 (17)	301 (37)	4 (28)	34 (76)	14 (17)	267 (30)

R ranking position, *H* H-index, *A* article count, *C* citation count

that *Ngee Ann Polytechnic* and *University of Malaya* were the closest collaborators, collaborating in 19 articles.

3.6 Analyses of major keywords and their evolutions

The keywords in an article usually represent the primary research focus, which helps to effectively explore the research topic of an article [58]. The 20 most frequently used keywords are listed in Table 6, among which "electroencephalogram" was ranked number one (appearing in 85 articles). Other frequent keywords included "brain-computer interface (50)" and "classification (38)." An annual trend analysis of research topics leveraging keywords used in the articles was conducted (see Fig. 6). During the years studied, the majority of keywords experienced a significant increase in frequency of use, in particular, "classification," "electroencephalography," "signal," "feature extraction," and "algorithm."

We further explored the evolution of the research topics in terms of frequency during the five periods of time (2009–2010, 2011–2012, 2013–2014, 2015–2016, and 2017–2018), by using five word clouds (see Fig. 7), in which the point size of the font indicates keyword frequency. The idea behind the use of a word cloud for the considered articles is that it enables us to analyze the most predominant keywords. Moreover, keywords of smaller point sizes may indicate future directions for research. A word cloud depicts keywords whose relative importance can be visualized through their size in the generated cloud. Figure 7a shows the word cloud for keywords appearing in more than 13 articles published during the period 2009–2010. It is clear that "classification," "epilepsy," and "communication" were the most predominant keywords, while "neural network," "support vector machine," "signal," and "model" were less predominant. Figure 7b displays the word cloud for keywords appearing in more than 13 articles published during the period 2011–2012. It can be seen that "classification," "support vector machine," "epilepsy," and "communication" were the most predominant keywords, while keywords such as "selection," "motor imagery," and "seizure detection" were less predominant. Figure 7c shows the word cloud for keywords appearing in more than 13 articles published during the period 2013–2014. It is clear that "classification," "support vector machine," "system," "epilepsy," "neural network," and "motor imagery" were the most predominant keywords, while keywords such as "artificial neural network," "feature," and "seizure detection" were less predominant. Figure 7d shows the word cloud for keywords appearing in more than 13 articles published during the period 2015–2016. It can be seen that "classification," "support vector machine," "signal," "electroencephalography," "system," "epilepsy," "motor imagery," "signal," and "feature extraction" were the most predominant keywords, while keywords such as "artificial neural network," "entropy," and "feature" were less predominant. Figure 7e shows the word cloud for keywords appearing in more than 13 articles published during the period 2017–2018. It is clear that "classification," "support vector machine," "system," "epilepsy," "neural network," and "motor imagery" were the most

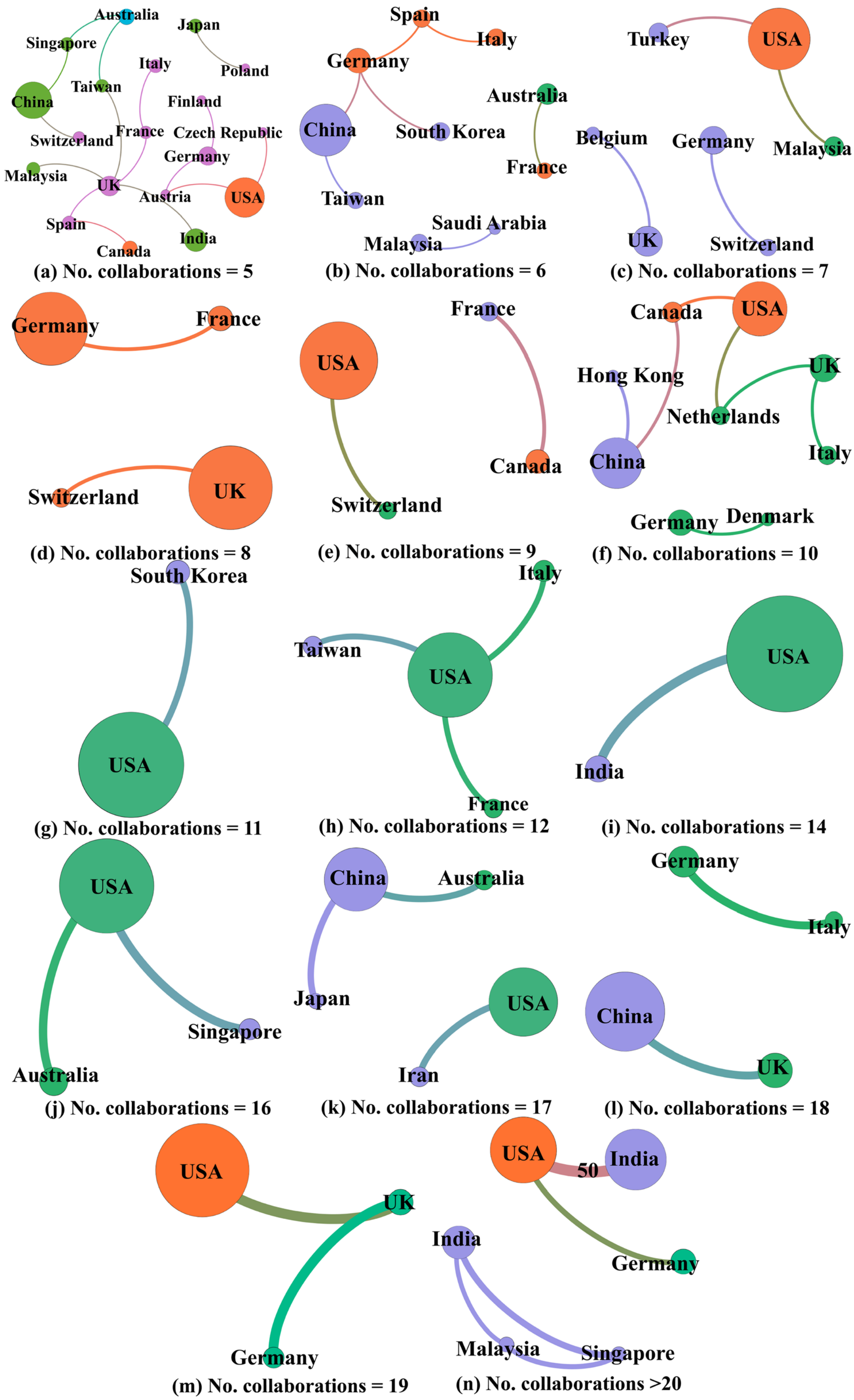

Fig. 4 Collaborative relationships between countries/regions

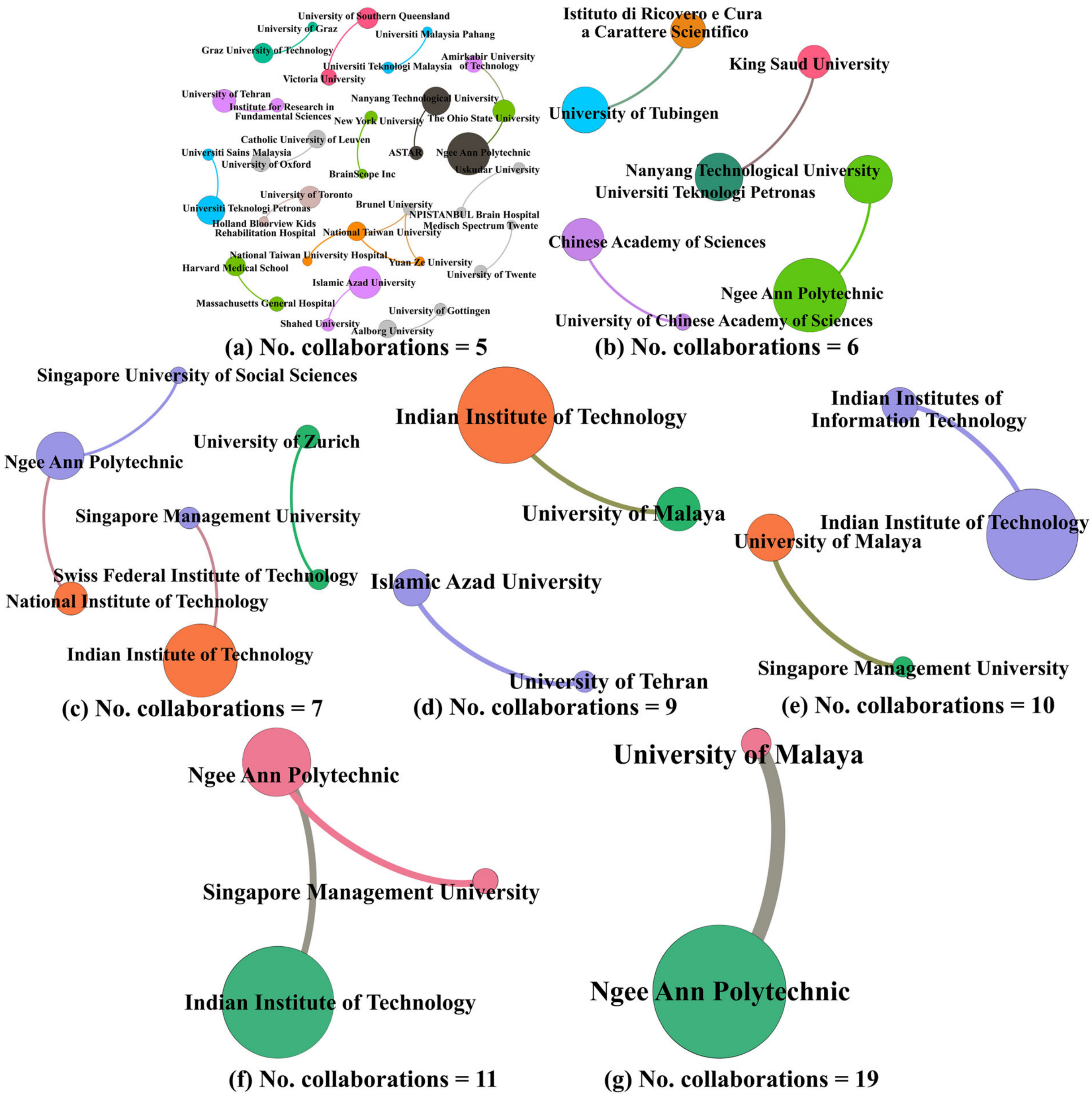

Fig. 5 Collaborative relationships between institutions

predominant keywords, while keywords such as "machine learning," "artificial neural network," and "feature selection" were less predominant. From the analysis, as time went by, research topics became more diverse, while keywords such as "classification" and "support vector machine" had always been the core focuses in the field. Several keywords drew an increasing amount of attention over time. For example, "electroencephalography" received increasing focus with time. The keyword "feature extraction" appeared in the period 2011–2012 and has gained increasing attention since then.

3.7 Major research topics and their evolutions

After filtering using term frequency-inverse document frequency, within the 2058 articles, the most frequently used was "seizure" (appearing in 456 articles, with a proportion of 22.21%), followed by "epileptic" (367, 17.88%), "imagery" (331, 16.12%), "movement" (301, 14.66%), "entropy" (252, 12.27%), and "attention" (182, 8.87%).

Table 7 shows the results of the 16-topic model, including representative terms, topical proportion, suggested labels, and the results of the topical Mann–Kendall (M–K) test [59, 60]. The top five most-discussed topics

Table 6 Top 20 frequently used keywords

Keyword	2009–2010		2011–2012		2013–2014		2015–2016		2017–2018	
	A	%	A	%	A	%	A	%	A	%
Electroencephalogram	85	49.42	112	51.14	153	51.34	273	51.12	416	50.12
Brain computer interface	50	29.07	66	30.14	92	30.87	173	32.40	212	25.54
Classification	38	22.09	51	23.29	71	23.83	146	27.34	260	31.33
Support vector machine	14	8.14	34	15.53	60	20.13	74	13.86	141	16.99
Electroencephalography	12	6.98	14	6.39	34	11.41	67	12.55	130	15.66
Signal	16	9.30	20	9.13	21	7.05	69	12.92	98	11.81
System	14	8.14	24	10.96	34	11.41	57	10.67	89	10.72
Epilepsy	19	11.05	28	12.79	28	9.40	46	8.61	95	11.45
Feature extraction	10	5.81	23	10.50	24	8.05	54	10.11	91	10.96
Motor imagery	8	4.65	15	6.85	34	11.41	45	8.43	80	9.64
Neural network	14	8.14	21	9.59	31	10.40	41	7.68	72	8.67
Algorithm	12	6.98	16	7.31	27	9.06	49	9.18	73	8.80
Brain	15	8.72	13	5.94	22	7.38	45	8.43	80	9.64
Recognition	11	6.40	13	5.94	29	9.73	35	6.55	65	7.83
Communication	23	13.37	29	13.24	22	7.38	38	7.12	40	4.82
Event related potential	14	8.14	17	7.76	23	7.72	40	7.49	45	5.42
Independent component analysis	12	6.98	11	5.02	23	7.72	40	7.49	53	6.39
Electroencephalogram signal	12	6.98	9	4.11	17	5.70	30	5.62	68	8.19
Performance	14	8.14	12	5.48	18	6.04	33	6.18	57	6.87
Model	19	11.05	13	5.94	17	5.70	33	6.18	45	5.42

A article count, % proportion

were *epileptic seizure detection* (10.58%), *brain–machine interface* (8.50%), *EEG classification* (7.76%), *mental disorders* (7.73%), and *emotion* (7.18%).

From the M–K trend test results, it can be seen that *alcoholism and anesthesia* shows a significant increase in proportion, while *cognitive control and performance* shows a significantly decreasing trend. The trend of the annual proportions of these topics and topic distributions are shown in Figs. 8 and 9. Figure 8 shows that there are several topics which have received increasing attention from academia in recent years, such as *alcoholism and anesthesia*, *emotion*, *epilepsy*, *fatigue driving*, and *sleep and sleep quality*. Comparatively, several topics have attracted decreasing attention from scholars in recent years, such as *brain–machine interface*, *EEG artifact removal*, and *neural network*. Figure 9 shows issues that have received the most attention each year; however, for almost all of the ten years, issues regarding *brain–machine interface* and *epileptic seizure detection* were always the top concerns for scholars. In 2013, most attention was paid to issues concerning *mental disorders*, *EEG classification*, and *neural network*. In 2017 and 2018, researchers tended to focus more on issues concerning *epileptic seizure detection* and *emotion*.

3.8 Topic distributions of major journals, countries/regions, and institutions

Figure 10 depicts the topic distributions of influential journals, countries/regions, and institutions based on the H-index. From a journal perspective (see Fig. 10a), there were several journals that showed a particular interest in the publication of articles concerning *epileptic seizure detection*, including *Expert Systems with Applications*, *International Journal of Neural Systems*, and *Biomedical Signal Processing and Control*. Two journals were especially interested in *brain–machine interface*: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* and *PLoS ONE*. *Neuroimage* was especially interested in issues concerning *signal and semantics* and *depression*. It is also worth noting the research enthusiasm for *EEG classification* in *Neurocomputing*.

From the country/region perspective (see Fig. 10b), several countries/regions showed a comparatively balanced interest across all 16 topics, particularly the USA, China, and the UK. As for the others, each country/region showed a particular interest in one or two topics. For example, three countries/regions (India, Singapore, and Turkey) had great enthusiasm for *epileptic seizure detection* issues. Two countries/regions showed a particular interest in issues concerning *mental disorders*: the Netherlands and Iran. It is

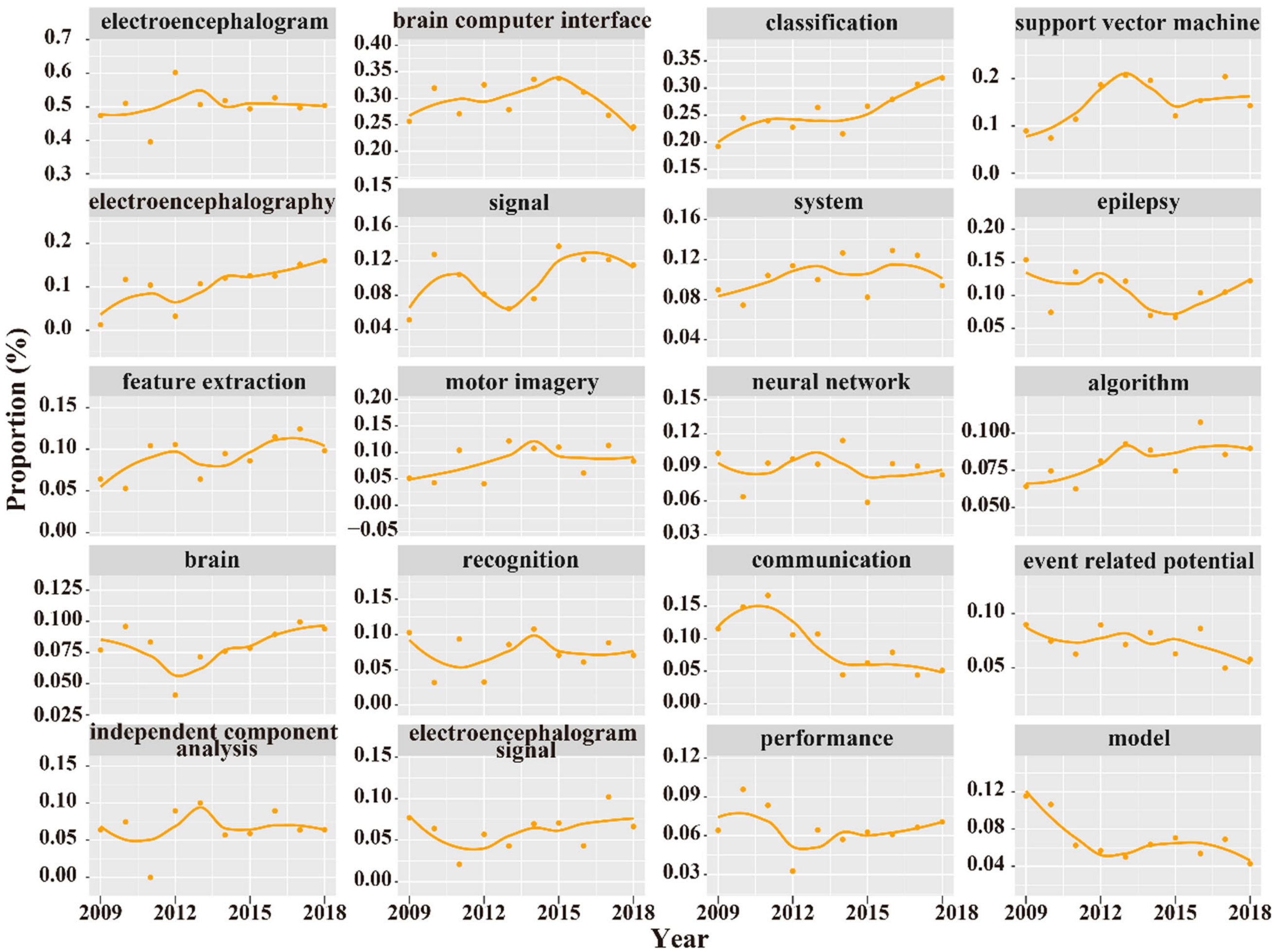

Fig. 6 Most frequently used keyword trends in articles from 2009 to 2018 (x-coordinate as year, y-coordinate as proportion %)

also worth noting the research enthusiasm for *brain–machine interface* in Germany.

Compared to countries/regions, institutions (see Fig. 10c) showed more interest in particular topics. For example, two institutions showed a particular interest in issues concerning *brain–machine interface*: *Graz University of Technology* and *University of Tubingen*. Second, two institutions were especially interested in issues concerning *mental disorders*: *The Ohio State University* and *Vrije Universiteit Amsterdam*. It is worth noting the research enthusiasm for *epileptic seizure detection* on the part of *Indian Institute of Technology* and *Ngee Ann Polytechnic*, as well as *alcoholism and anesthesia* on the part of *University of Malaya*. In addition, *University of California San Diego* showed a great interest in issues concerning *emotion*.

3.9 Topic differences in funding and international collaborations

We further explored the topic distributions concerning AI-enhanced human EEG analysis based on funding and international collaboration (see Fig. 11). Figure 11a shows the effect of funding on topic proportions, in which topics on the left were frequently mentioned in funded articles, while topics on the right appeared more in nonfunded articles. Six topics, namely *epileptic seizure detection*, *alcoholism and anesthesia*, *sleep and sleep quality*, *EEG artifact removal*, *neural network*, and *epilepsy*, were mentioned more frequently in funded articles, whereas eight topics, namely *brain–machine interface*, *depression*, *cognitive control and performance*, *EEG spectral analysis*, *emotion*, *signal and semantic*, *EEG classification*, and *vision*, were mentioned more frequently in nonfunded articles. Similarly, Fig. 11b shows the effect of international collaboration on topic proportions. Six topics, namely *brain–machine interface*, *epileptic seizure detection*, *cognitive control and performance*, *EEG artifact removal*,

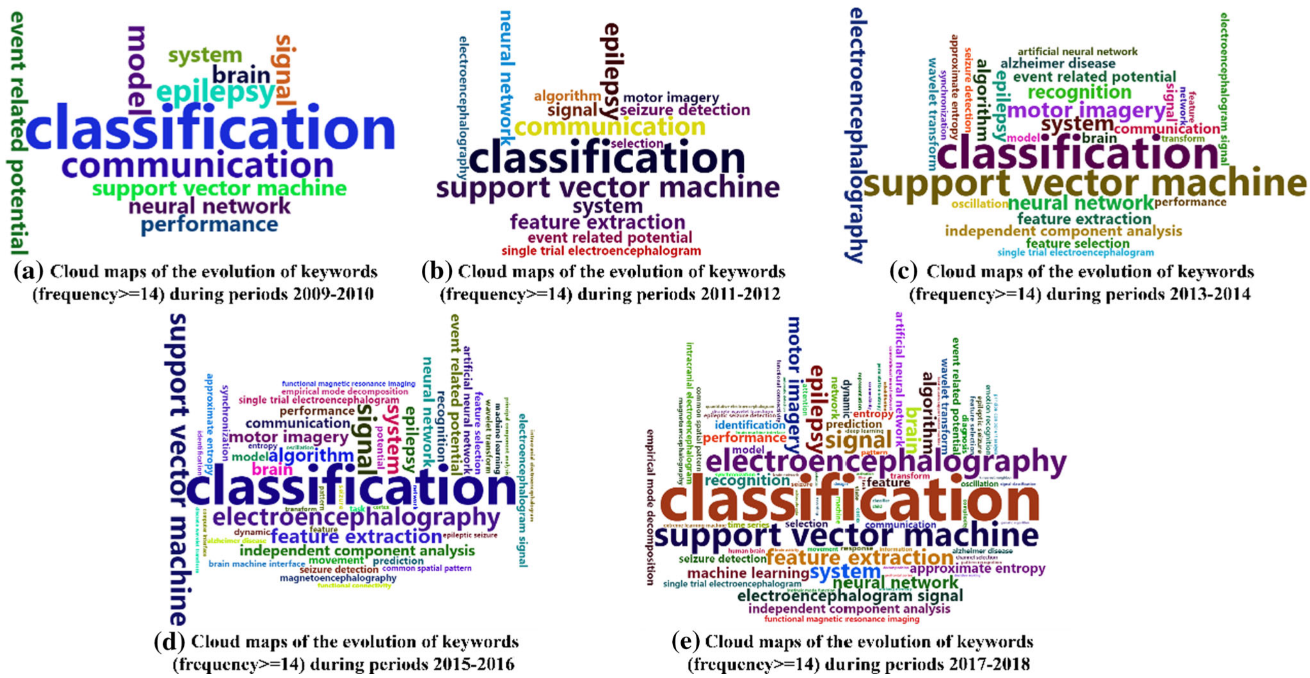

Fig. 7 Cloud maps showing the evolution of keywords

neural network, and *EEG classification*, were mentioned more frequently in articles collaborated on by more than one country/region. Comparatively, ten topics, namely *fatigue driving*, *depression*, *alcoholism and anesthesia*, *EEG spectral analysis*, *emotion*, *sleep and sleep quality*, *signal and semantics*, *epilepsy*, *mental disorders*, and *vision*, appeared significantly more in articles contributed by a single country/region.

4 Discussion

Early in the twentieth century, the application of AI technologies in human brain research has increased, e.g., pattern classification techniques in EEG data analysis [61]. EEG signals are effective for adoption into highly secure biometric systems because of their universality, uniqueness, and robustness [62]. Thus, they are commonly used to study brain activity [63]. In this study, bibliometric analysis, word cloud analysis, and STM were used to analyze and map the scientific literature concerning AI-enhanced human EEG analysis. Based on 2053 research articles collected from the SCI and SSCI databases, we provide a thorough review of the field by identifying influential countries/regions, institutions, and journals, as well as uncovering and visualizing scientific collaborations and detecting the evolution of major topics during the period 2009–2018.

The research articles and citations regarding AI-enhanced human EEG analysis have increased consistently over the studied period. Such findings demonstrate that the research field has received a significant increase in the amount of research interest and enthusiasm from academia. The analysis of the countries/regions has highlighted the contributions of the USA, China, and India in stimulating the development of the research field. From an institution perspective, *Indian Institute of Technology* has contributed the most in terms of both research output and research impact. The results of the journal analysis reveal a number of sources dealing with AI-enhanced human EEG analysis.

4.1 Insights from keyword analysis

Keyword analysis uncovered major research topics over five time periods, namely 2009–2010, 2011–2012, 2013–2014, 2015–2016, and 2017–2018. The 2053 research articles were variously dispersed with interests across diverse issues. Such analysis was useful for understanding the research focuses in each period, as well as the evolution of the field over the years. Thematic features concerning research on AI-enhanced human EEG analysis were uncovered through analysis of the keywords, with several ones of note being elaborated as follows.

On the whole, research issues in the field have grown more diverse as time has gone on, while several keywords captured common themes throughout the whole period. First, "electroencephalogram" was used the most in articles across the five time periods, along with "electroencephalography" and "electroencephalogram signal." This indicates that the majority of the studied articles involved

Table 7 Discriminating terms, topic proportions, suggested labels, and trend test results

Label	Representative terms	%	p	Trend
Epileptic seizure detection	Preictal, Freiburg, seizure, epileptic, Lyapunov, ictal, exponent, seizure-free, accelerometry, precursor	10.58	0.2831	↓
Brain–machine interface	Exoskeleton, movement-related, brain-robot, robotic, walking, spinal, cord, extremity, spinal-cord-injury, grasping	8.50	0.3711	↓
EEG classification	Spatial-patterns, type-2, c-means, Riemannian, Hopfield, multiclass, neuro-fuzzy, regularization, converter, fuzzy	7.76	1.0000	↓
Mental disorders	Alzheimer's, dementia, ad, autism, ADHD, Parkinson's, mci, attention-deficit/hyperactivity, frontotemporal, autistic	7.73	1.0000	↓
Emotion	Emotion, emotional, affective, clip, unpleasant, gist, pupil, pleasant, decision-level, angry	7.18	0.2105	↑
Neural network	Hermite, flickering, interpolation, CNN, particle, deep, swarm, SSVEPS, steady-state, convolutional	7.15	0.8580	↓
Signal and semantics	Source-space, in vivo, beamformer, pain-evoked, post-stimulus, verb, Bayesian-inference, neucube, CLZ, spoken	6.90	0.8580	↑
Epilepsy	Epileptogenic, intracerebral, IED, epileptiform, HFOS, HFO, resection, epilepsy-related, dysplasia	6.26	0.1524	↑
depression	Reward, MDD, FRN, tinnitus, antidepressant, ganglion, migraine, punishment, depression, RTMS	5.98	0.3711	↑
Alcoholism and anesthesia	Alcoholism, anesthesia, IMF, anesthetic, alcoholism, tunable-q, general-anesthesia, three-band, unconsciousness, HHT	5.78	0.0491	↑↑
EEG artifact removal	Artifact, removal, ocular, artefact, schizotypy, artifactual, ABC, immune, covariate, VG	5.18	0.3711	↓
Fatigue driving	Fatigue, driver, drowsiness, driving, drowsy, sleepiness, sickness, LZC, delirium, headband	5.05	0.1074	↑
Cognitive control and performance	Spelling, p300-based, concealed, multi-objective, deception, guilty, bootstrap, melatonin, p300, chloral	4.68	0.0491	↓↓
Sleep and sleep quality	Sleep, staging, microstate, multifractal, microstates, spindle, maturation, REM, polysomnography, REM-sleep	4.37	0.4743	↓
Vision	Familiarity, n170, image, object, vision, RSVP, tactile, face, texture, shape	4.00	0.5915	↓
EEG spectral analysis	Appraisal, grading, AEEG, amplitude-integrated, hypsarrhythmia, pleasantness, ERRPS, MMN, tool-gesture, Pregabalin	2.91	0.8580	↓

Topics are ranked in descending order of proportion. Full names of abbreviations are shown in Table S2 in Appendix. ↑(↓): increasing (decreasing) trend but not significant ($p > 0.05$); ↑↑(↓↓), ↑↑↑(↓↓↓), ↑↑↑↑(↓↓↓↓): significantly increasing (decreasing) trend ($p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively

the use of EEGs in human brain research. Second, "classification" was also used frequently in the field, due to the wide application of diverse classification algorithms in disease diagnosis and medical data analysis. In studies applying AI in the diagnosis of diseases, classification was the final goal, while in other research work, classification was used as part of the data analysis [64]. Third, a majority of the studies targeted "brain-computer interface (BCI)." BCI has always been among the top three most frequently used keywords, indicating a great research interest among scholars. For example, Lawhern [65] described EEGNet as an innovative, compact convolutional neural network (CNN) for EEG-supported BCIs. In comparison with state-of-the-art approaches, it was found that EEGNet performed better.

In addition, several AI technologies were highlighted by keyword analysis. Support vector machine (SVM) was the most frequently applied algorithm over the studied period, with the proportion rising from 8.14% in 2009–2010 to 16.99% in 2017–2018. Machine learning gained increased research interest, with the proportion rising from 2.91% in 2009–2010 to 7.47% in 2017–2018, indicating a growing interest in applying machine learning technologies for human EEG analysis. For example, Hsu et al. [66] aimed at investigating the potential of EEG signals for classifying imaginary lower limb stepping movements and in designing robust motor imagery classifiers based on an SVM. "Deep learning" appeared in two articles in 2015–2016 and, since then, has continued to gain increasing interest among authors, appearing in 24 articles in 2017–2018. This reflects a rapidly increasing interest among scholars in utilizing deep learning technologies for human EEG analysis. For example, Kose [67] described a hybrid system developed with the use of ANNs and an antlion optimizer.

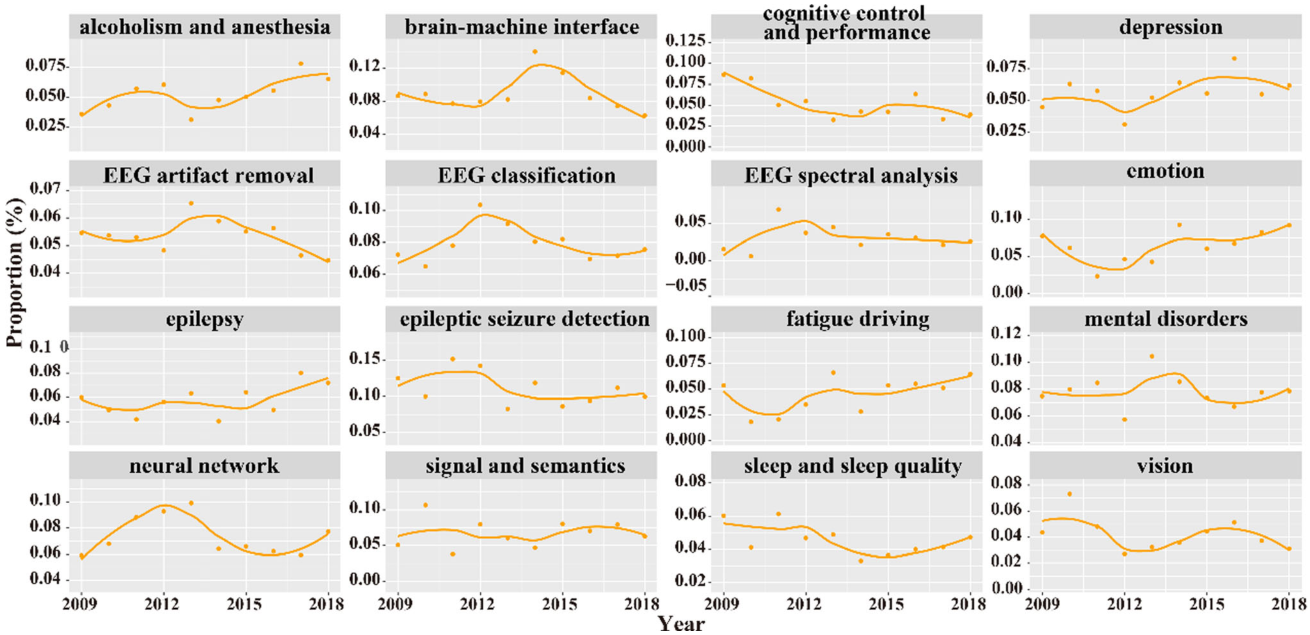

Fig. 8 Annual topic proportion

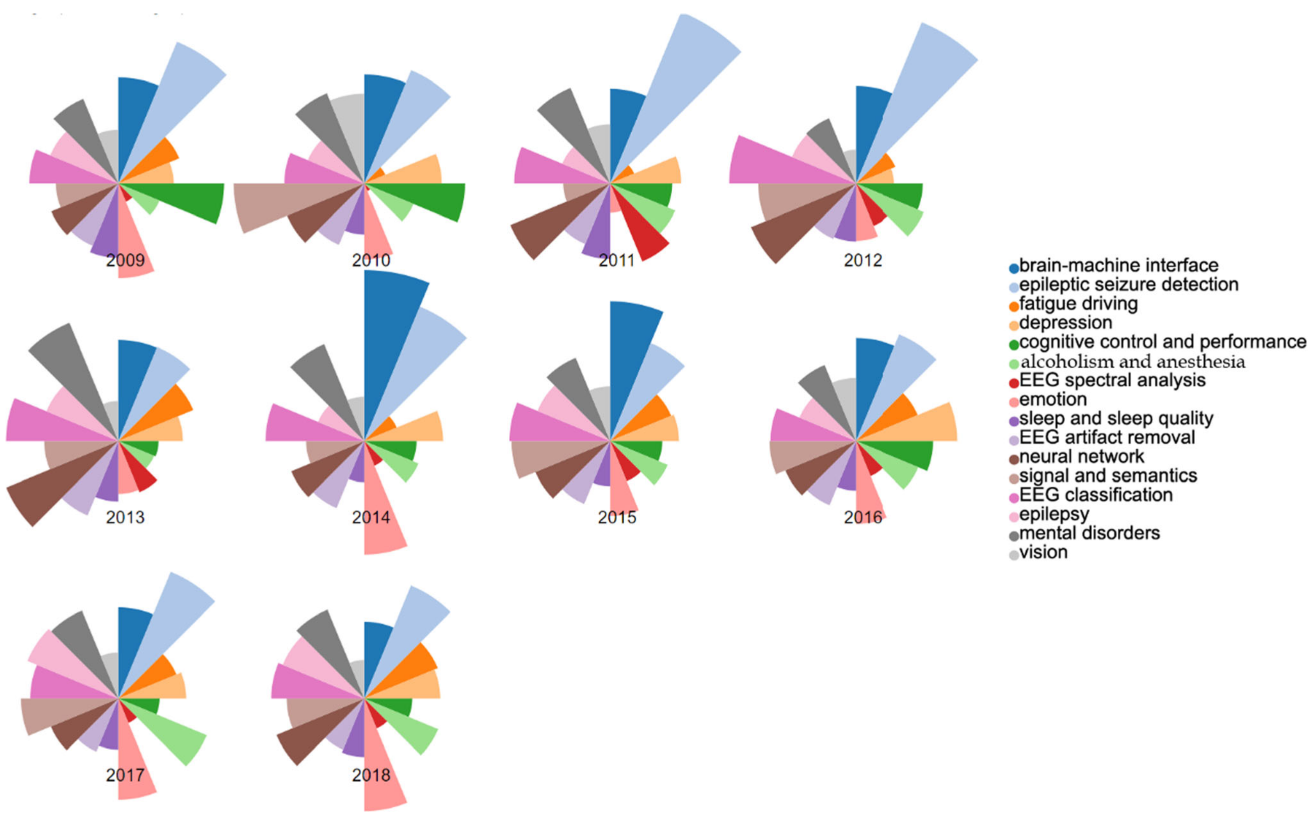

Fig. 9 Annual topic distribution

Experiments indicated that the proposed system was capable of future state prediction, with even better performance than hybrid ANN-driven systems. Muhammad et al. [68] proposed a novel automated seizure detection system, in which EEG signals from a head-mounted set were recorded and processed by CNNs. Goh et al. [69] presented a deep neural network topology called spatio-spectral representation learning, to learn spatial and spectral

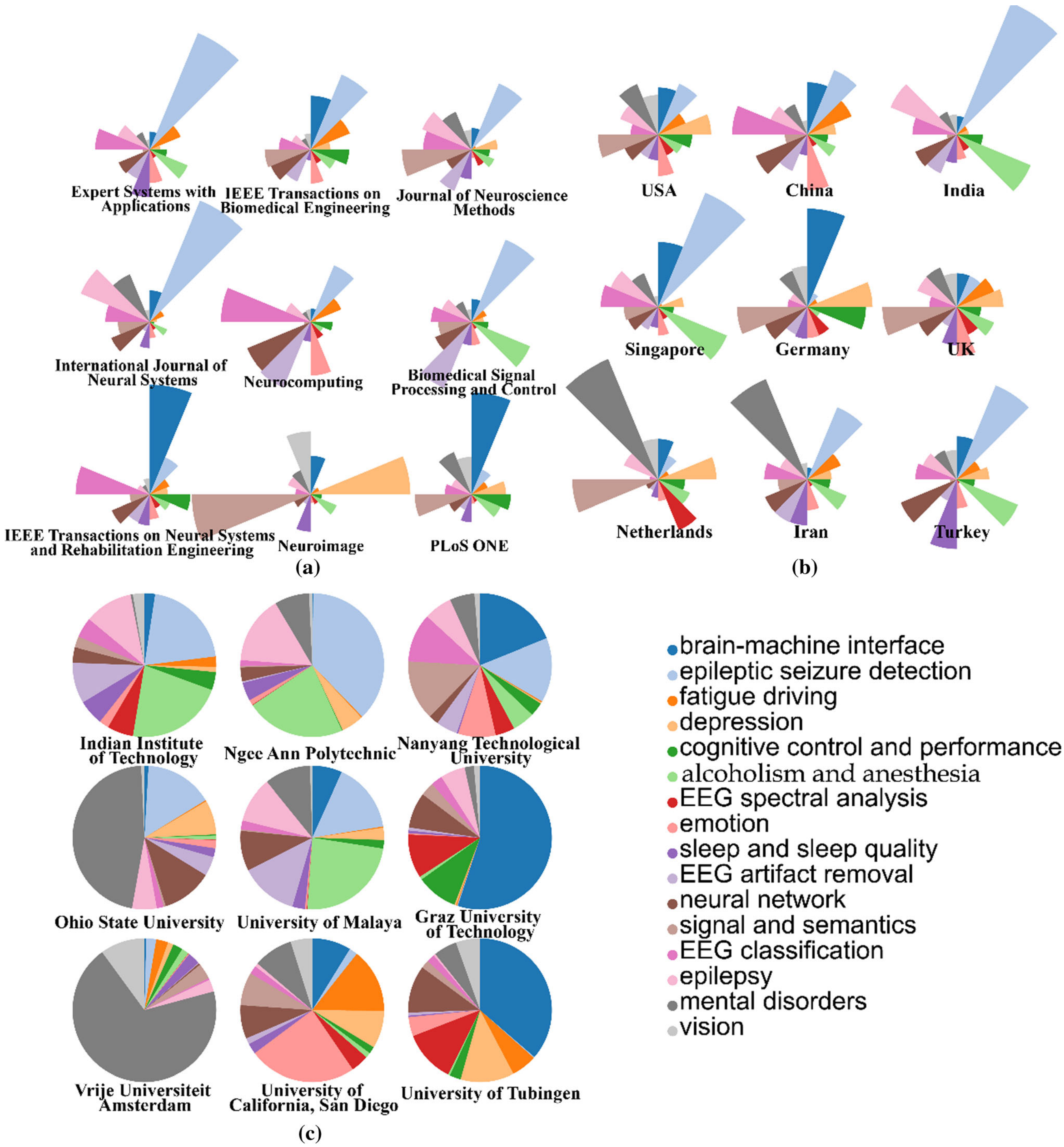

Fig. 10 Topic proportion distributions of influential journals (**a**), countries/regions (**b**), and institutions (**c**)

representations of EEG signals from multiple channels while walking. Experiments indicated the effectiveness of the topology in facilitating human locomotion decoding, which provided significant insights into exoskeleton design, rehabilitation processes, and clinical diagnosis.

For example, an SVM, with its many distinctive features, such as its usability, small sample size, and global optimization, is popular in EEG research. However, many scholars have pointed out that SVM algorithms show poor performance in large-scale datasets. Moreover, due to the fast growth of EEG data, the accuracy of traditional SVM models may decline, since they are incapable of effectively processing sizable data. As a result, deep learning algorithms have been the focus of new research because of their

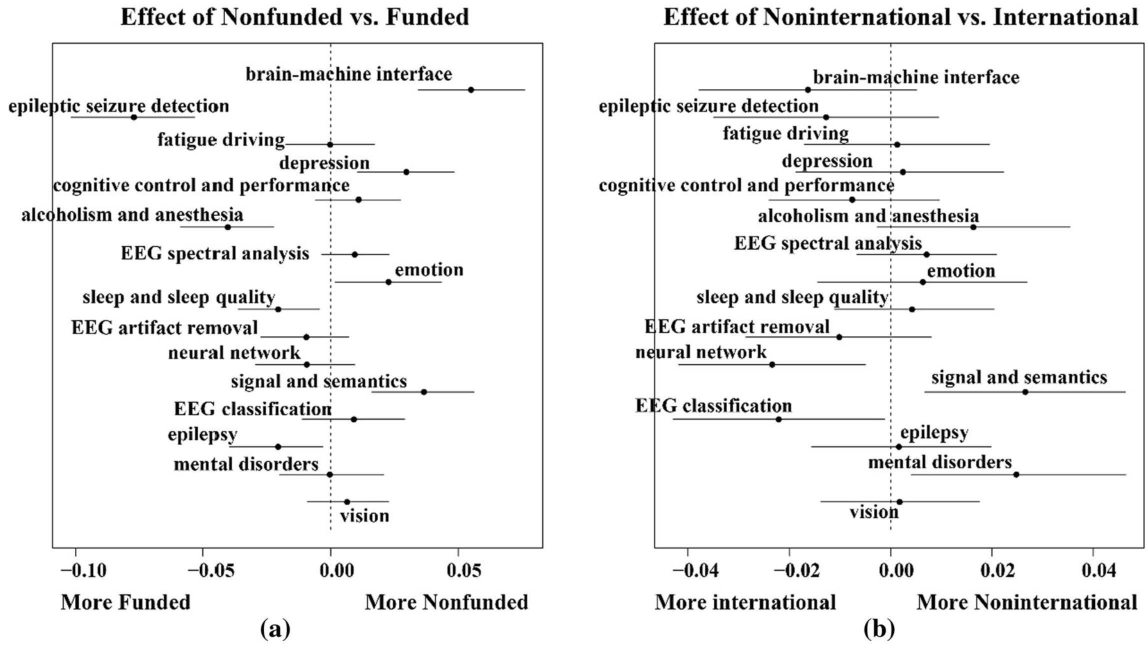

Fig. 11 Effects of funding (**a**) and international collaborations (**b**) on topic proportions

noteworthy ability of EEG feature representation. Furthermore, deep learning algorithms work with fewer feature sets in comparison with SVM algorithms [70]. Hence, recently, deep learning algorithms have also successfully been adopted for physiological signal processing, such as EEGs, and have achieved good performance. Nevertheless, their comparatively higher complexity is a potential issue [71]. Specifically, deep learning algorithms usually require expensive computational devices such as high-ended GPUs. As such, deep learning algorithms may not be ideal for EEG analysis [72].

Nevertheless, SVMs and deep learning serve as two popular tools for EEG analysis in a variety of applications. Table 8 summarizes the comparison of SVMs and deep learning in our data corpus. From the table, it can be seen that in most of the studies (e.g., [73–75]), deep learning algorithms show better performance than SVMs in terms of accuracy, although with more computational time. However, studies did demonstrate the higher accuracy of SVMs over deep learning, most of which were related to EEG classification concerning meatal disease, particularly epilepsy (e.g., [76–78]).

Another research focus was "epilepsy." For example, Sharma and Pachori [92] presented a system for automatically detecting epileptic episodes. This system implemented a tunable-Q wavelet transform for EEG signal decomposition into different sub-bands. Amorim et al. [93] introduced an innovative algorithm for epilepsy detection based on shearlet and contourlet transforms for EEG signal decomposition into frequency bands. Sairamya et al. [94] presented an innovative method for epilepsy detection by applying (symmetrically weighted) local neighbor gradient patterns. The keyword "feature extraction" also gradually received increasing attention. For example, Chen et al. [95] proposed an innovative feature extraction approach with the use of different entropies to express EEG characteristics.

Other frequently used keywords such as "model," "algorithm," "system," and "performance" were related to research by focusing on the improvement of models and algorithms. In these cases, brain signals were commonly used to verify the accuracy of algorithms. For instance, Wang et al. [96] presented an innovative approach through a combination of a Gaussian mixture and genetic algorithms to detect abnormal EEG samples. The term "performance" in "cognitive performance" indicated scores obtained by subjects in cognitive tests. The correlation between these behavioral indicators and brain signals could also be used as a diagnostic predictor [97].

4.2 Insights from the topic modeling analysis

The findings from the topic modeling analysis also provide implications about the predominant issues concerning AI-enhanced EEG analysis among scholars. There were several topics with which the community was most concerned. For example, seizure prediction based on EEG signal analysis received significant attention [98]. However, due to the unpredictability of occurrence, the detection and treatment of epileptic seizures are difficult [99]. Thus, it is of great urgency to develop reliable and effective seizure prediction algorithms and, at the same time, minimize the

Table 8 Comparison of SVM and deep learning in EEG studies

References	Purpose	Algorithm	Result
Gandhi et al. [73]	EEG signal classification	SVM, probabilistic neural network (PNN)	The accuracy of classification for SVM was less and computational time was more compared to the PNN classifier
Tang et al. [74]	Motor imagery classification	SVM, CNN	CNN was better than SVM in terms of accuracy
Jaiswal and Banka [75]	Epileptic classification	SVM, ANN	ANN was higher than SVM in terms of accuracy, while time cost was higher than in SVM
Acharya et al. [76]	Automated epilepsy diagnosis	SVM, PNN	SVM was better than PNN in terms of accuracy
Nunes et al. [77]	Epilepsy diagnosis	SVM, ANN	SVM was better than ANN in terms of accuracy and time cost
Ng et al. [78]	Automated epileptic identification	SVM, radial basis PNN	SVM was superior to PNN in terms of accuracy
Zheng and Lu [79]	EEG-based emotion recognition	SVM, deep belief networks (DBNs)	The DBN model achieved 2.09% higher accuracy and 1.38% lower standard deviation than SVM
Şen et al. [80]	Sleep stage classification	SVM, feed-forward neural network (FFNN)	SVM was faster than FFNN and achieved higher accuracy than FFNN
Yuvaraj et al. [81]	Parkinson's disease diagnosis	SVM, PNN	SVM was better than PNN in terms of accuracy
Bascil et al. [82]	Spectral feature extraction of EEG signals	SVM, multilayer neural network (MLNN), PNN	LS-SVM was superior to linear SVM in terms of classification results and computational time; PNN had the best accuracy rate compared to MLNN
Faust et al. [83]	Depression diagnosis	SVM, PNN	PNN was better than SVM in terms of accuracy
Li et al. [84]	Brain–machine interface control	SVM, small-world neural network (SWNN)	SWNN was better than LS-SVM in terms of accuracy
Hsu [85]	Motor imagery classification	SVM, back-propagation neural network (BPNN)	SVM classifier was better than BPNN in MI classification
Ren et al. [86]	Seizure classification	SVM, BPNN	BPNN was superior to SVM in terms of accuracy
Ahmad et al. [87]	Epilepsy diagnosis	SVM, ANN	SVM was better than ANN in terms of accuracy
Zeng et al. [88]	Driver mental state classification	SVM, LSTM, CNN	CNN was higher than SVM in terms of accuracy
Hong [89]	Multimodal BCIs	SVM, multilayer perceptron (MLP) neural network	SVM was superior to MLP-NN in terms of accuracy
Narang et al. [90]	Epileptic seizure classification	ANN, SVM	ANN classifier was superior to SVM in terms of accuracy
Antelis et al. [91]	Motor task recognition	SVM, dendrite morphological neural networks (DMNN)	DMNN was superior to SVM

computational requirements [98]. Furthermore, there is a need to develop automated systems that are able to characterize EEG-based epileptic activities to enable patients and clinicians to take proper action based on essential clinical information [99]. A variety of approaches have been developed for epileptic activity detection using EEG signals. For instance, Sriraam et al. [100] focused on epileptic seizure detection from EEG signals across multiple channels with the use of an automatic supervised BPNN algorithm.

Second, scholars have recently focused on the development of BCIs for people with physical disabilities to interconnect with EEG-based peripheral applications. EEGs have been effective in the investigation of patients' health and brain physiological activities [101]. BCIs use EEG signals to make decisions and generate control signals [102]. In recent years, motor imagery EEG-based BCIs have received great attention from scholars in a variety of areas, for example, medicine and engineering [103]. While voluntary motor intention detection from EEGs has been increasingly used to trigger external devices in closed-loop BCI research [104]. BCIs are capable of decoding neurophysiological brain signals, which are further translated into signals to control peripheral devices such as wheelchairs [105]. In addition, brain–machine interfaces (BMIs) enable people with serious motor impairments to control peripheral devices such as prosthetic arms [106] with great independence through the direct translation of brain activity into commands. EEG-based BMIs have proven to have promising applications for motor disabled individuals [105], stroke rehabilitation [107], and people with paralysis [108].

Third, EEGs are a prevalent technique used for recording brain activity. However, due to the low signal-to-noise ratio, motor imagery classification is a tricky problem. Therefore, how to select the most discriminative features is critical to enhancing classifiers' performance [109]. Most relevant studies were found to be related to EEG classification in the application of BCIs. As indicated by Li and Wen [110], motor imagery classification served as a crucial basis for BCIs design. Numerous efforts have been made on EEG signal classification for motor imagery-BCI, [111]. For instance, Zheng et al. [112] proposed an innovative multiclass EEG classifier aimed at enhancing the accuracy of classification in EEG-driven BCIs involving multiple mental activities.

Furthermore, alongside AI technologies, EEGs have been widely adopted in the study of issues concerning mental disorders. For instance, Garn et al. [113] developed and evaluated a classifier based on quantitative EEG features for differential diagnosis between patients with diseases such as Alzheimer's and Parkinson's. Metin et al. [114] applied quantitative EEGs to differentiate frontotemporal dementia from late-onset bipolar disorders through the use of an ANN and a genetic algorithm-based method. Additionally, EEGs offer promising alternatives to the development of effective and affordable biomarkers for mental disorders because of the low cost, portability, and robustness [115].

Research into emotion recognition using EEGs has become increasingly active [116]. However, such a task is difficult because of the poor feature generalizability across subjects [117]. Emotion is a crucial part of human behavior. Hence, its incorporation into the reasoning module of intelligent systems aimed at anticipating and responding to human reactions would make a great difference [118]. Emotion classification and assessment from EEG data has also attracted much attention through the rapid development of dry electrode techniques, machine learning algorithms, and various real-world applications of BCI [119, 120]. By analyzing EEGs derived from responses in automated nervous systems, computers will be capable of assessing users' emotions and determining correlations between EEG features and emotions. Thanks to advances in signal processing technologies, the evaluative ability of human emotions shows exponential growth with increasingly available EEG signal features [118].

4.3 Insights from topic trend analysis

Several topics have received increasing interest from academia in recent years, in addition to the emotional and mental disorders discussed in Sect. 4.2. First, the research community has shown interest in issues concerning alcoholism and anesthesia. On the one hand, alcohol is a severe intoxication substance that changes the brain's functionality by disturbing the neuronal process of the central nervous system, thereby resulting in mental and behavioral disorders [121]. Alcoholism is an essential disorder concerning central nervous systems that results from heavy drinking and has been regarded as a global social and health issue [122]. More importantly, the screening of patients with alcoholism has been challenging due to the subjectivity imparted by self-test reports. Automatic methods involving neuroimaging modality such as quantitative EEGs have demonstrated encouraging effects [123]. For example, Sharma et al. [122] presented a novel automated system for classifying alcoholic and normal EEG signals. On the other hand, it is essential to monitor and administrate anesthesia depth to avoid patients from being aware during clinical operations [121, 124, 125]. The EEG spectrum has the potential to predict anesthesia depth through the use of various signal processing approaches [126]. For example, Liang et al. [127] presented a novel classifier for spectral EEG pattern classification among patients undergoing sevoflurane general anesthesia, using a genetic algorithm—SVM.

Second, as a prevalent mental illness, depression relates to emotional changes [128] and is frequently linked to a sense of guilt, self-abasement, inattention, and at the very worst, showing suicidal tendencies. Depressive disorders can be clinically and pathophysiologically heterogeneous. A potentially promising tool to parse such heterogeneity is endophenotypes [129]. Compared to expensive MRI machines, EEGs are a favored diagnostic tool because of their noninvasiveness, economy, and handleability. Moreover, EEGs record the brain's electrical activities over a longer period of time than MRI machines' recording of blood changes in the brain [130]. Hence, EEGs are broadly used when studying and diagnosing a variety of neurological disorders. For example, Shahsavar et al. [131] aimed to assess patients' brain activity during severe depression by applying transcranial direct current stimulation based on event-related potentials. Acharya et al. [130] proposed an innovative computational approach for EEG-driven depression screening using CNNs.

Third, there was an increase in interest in using AI technologies for epilepsy diagnosis based on EEGs. Epilepsy is a common and serious brain disorder, with a complex set of possible phenotypes ranging from pathologic abnormalities to variations in EEGs, while the burden of epilepsy brings with it huge costs [132]. The simultaneous use of EEGs along with functional magnetic resonance imaging (EEG-fMRI) is promising in mapping epilepsy [133]. The effectiveness of EEG-fMRI as a non-invasive localizing technique in evaluating epilepsy pre-surgically has been widely proven [134]. In addition, scalp EEG recordings and the classification of interictal epileptiform discharges in epilepsy patients offer rich information concerning epileptogenic networks [135]. A great number of studies concerning the use of AI-enhanced EEG analysis for epilepsy are available. For example, Varatharajah et al. [136] reported an AI-driven technique that combined multiple interictal electrophysiological biomarkers and their temporal features in the identification of seizure onset zones in patients undergoing drug-resistant epilepsy evaluation.

Fourth, driver drowsiness is a primary cause of fatal accidents, injury, and property damage and has become an active area of research [137]. Drowsiness can be detected by physiological signals monitored during driving, thereby linking drowsiness to changes in corresponding EEG patterns [138]. Thus, recent studies have begun to explore the implementation of EEGs as part of driving assistance systems to detect driver drowsiness [139]. Hence, highly accurate systems that are able to monitor and detect driver fatigue are valuable measures for decreasing fatigue-associated road accidents [140]. Recently, numerous analytical approaches have been applied to EEGs to quantitatively detect fatigue state [141]. Driving information concerning drivers' physiological signals, such as EEGs and eye-tracking, are commonly used [142].

In addition to the wide application of existing neural network algorithms, a growing number of novel neural network approaches have been proposed, especially in regard to EEG analysis. For example, Waytowich et al. [143] explored how compact CNNs could decode raw EEG signals without user-specific calibration. Kose [67] proposed an innovative hybrid system for dealing with EEG time series, with the use of an ANN and an antlion optimizer.

There has also been a growing interest in issues concerning sleep and sleep quality. Sleep evaluation through sleep stage analysis is essential in clinical practices [144]. The effectiveness of sleep staging has been proven for auxiliary diagnosis of sleep diseases and relevant psychiatric disorders [145]. Visual sleep scoring enables a tangible and initial understanding of the changes in brain waves in each sleep stage [146]. Automatic sleep scoring is essential because large-scale data needs to be visually explored by experts, and such a procedure can be time-consuming, subjective, and error-prone. Thus, many scholars have spent a great deal of effort in facilitating automated classification and analysis of sleep stages. For example, Alickovic and Subasi [147] proposed a robust system for automatic sleep stage classification from single-channel EEGs by using multiscale principal component analysis, discrete wavelet transforms, and a rotational SVM.

4.4 Connections between keyword results and topic analyses

We also highlight the connections between the keyword and topic analyses in terms of similar results and techniques used in each topic.

There are several similar findings regarding frequently used keywords and topics. First, the significance of classification was highlighted by both types of analyses, with frequent usage of the keyword "classification" and the identified topic *EEG classification*. Second, the frequent use of "brain-computer interface" and the widely researched topic *brain–machine interface* indicated the popularity of BCI and BMI in EEG research. Third, the significance of AI in EEG research can be seen by the increased attention paid to issues concerning "deep learning" and *neural network*. The frequent use of "epilepsy" and the identification of two popularly researched topics *epileptic seizure detection* and *epilepsy* indicated that epilepsy was an important area of research in EEG studies.

We also explored the major techniques/algorithms and their evolutions in each of the 16 topics. For each topic, based on the top 50 representative articles, the keywords were identified and imported into VOSviewer[4] for analysis. The results are shown in Fig. 12, where the node color represents the average publication year. There are a number of important implications that can be obtained from the results.

First, for most of the topics, classification played a significant role, particularly for *brain–machine interface*, *EEG spectral analysis*, *sleep and sleep quality*, and *EEG classification*. However, the significance of classification and its prevalence in usage for each topic was not synchronous. For some topics, classification demonstrated its research value in the early stages. For example, classification was popular in research on EEG spectral analysis mainly in 2013. As for topics such as *epileptic seizure*

[4] https://www.vosviewer.com/.

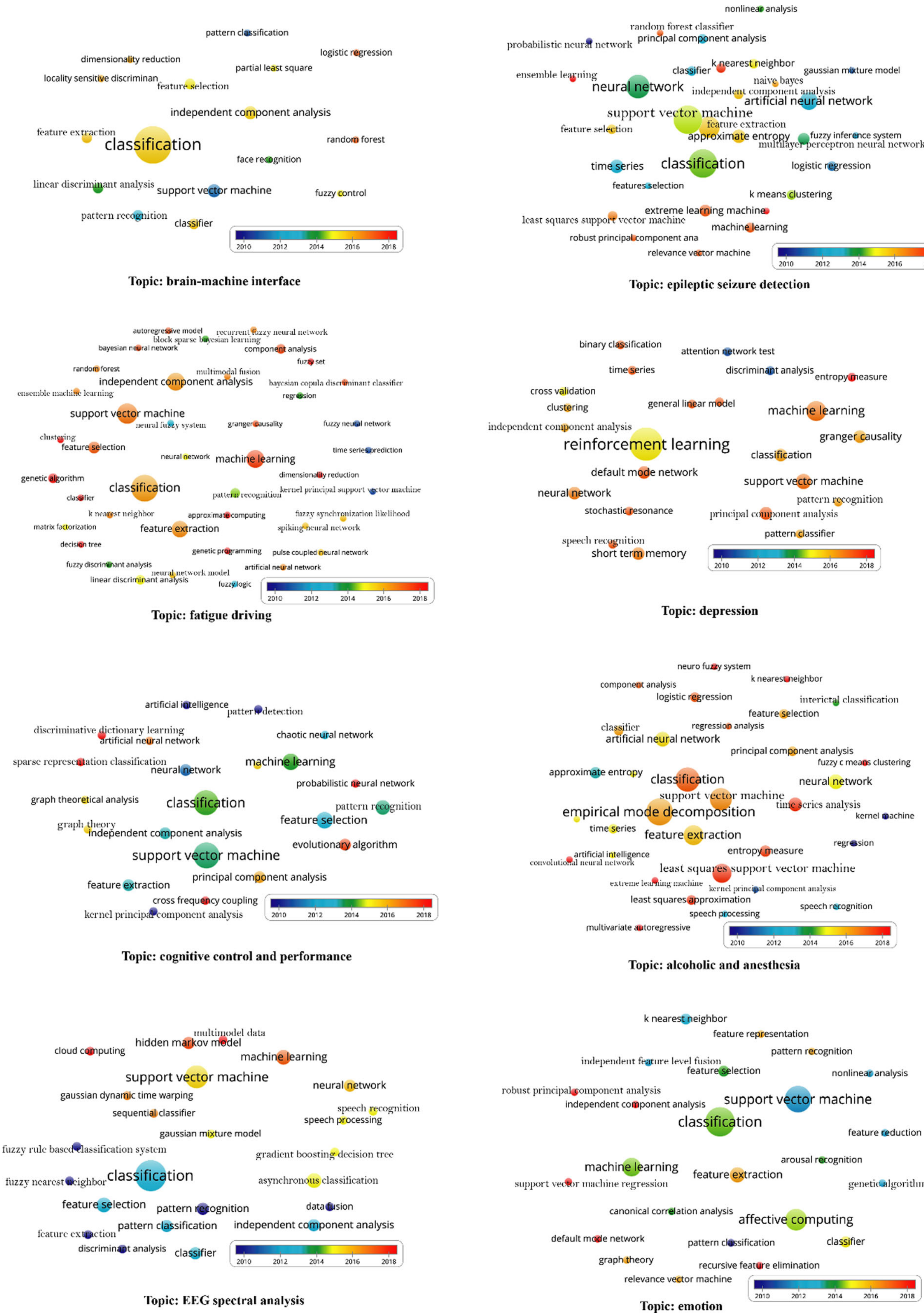

Fig. 12 Technique/algorithm trends used in each of the 16 topics

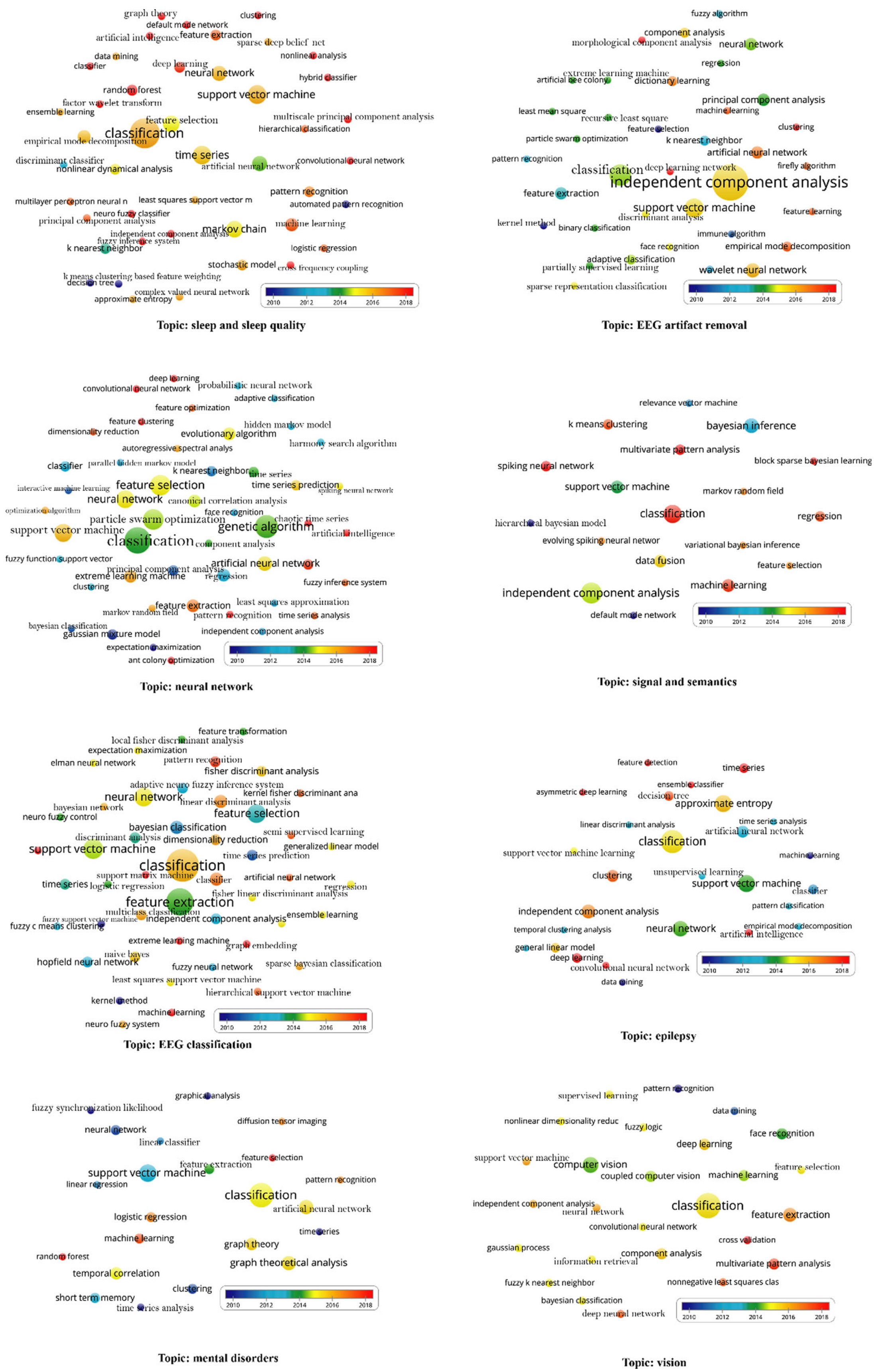

Fig. 12 continued

detection, *cognitive control and performance*, *emotion*, *EEG artifact removal*, and *neural network*, the prevalence of the adoption of classification algorithms mainly appeared in 2014. Furthermore, the use of classification algorithms in research on *epilepsy*, *mental disorders*, and *vision* was particularly highlighted in 2015. On the contrary, for some topics, classification mainly received significant attention in the later stages. For example, it was not until 2016 that classification became popular among research devoted to *brain–machine interface*, *fatigue driving*, *sleep and sleep quality*, and *EEG classification*. In addition, researchers have shown great interest in the use of classification algorithms in research on *alcoholism and anesthesia*, as well as *signal and semantics*, particularly since 2018.

Second, the popularity of techniques/algorithms used in each of the 16 topics was inconsistent. On the one hand, several topics showed interest in the use of various types of techniques, for example, *sleep and sleep quality*, *EEG classification*, *neural network*, *fatigue driving*, *EEG artifact removal*, and *alcoholism and anesthesia*. Such topics can be treated as technology-driven topics. On the other hand, other topics seemed to depend less on the adoption of techniques, with fewer types of techniques/algorithms being involved, for example, *brain–machine interface* and *signal and semantics*.

Third, for most of the 16 topics, increasingly more techniques received attention from researchers and were increasingly involved in research as time went on. Most importantly, there was a significant tendency in the growing use of advanced techniques in various aspects of EEG research, particularly for technology-driven topics such as *sleep and sleep quality* and *EEG classification*. Specifically, statistical algorithms and basic AI techniques (e.g., SVMs, decision trees, *k*-means clustering, time series analysis, independent component analysis, Bayesian classification, linear regression, clustering, principal component analysis, k-nearest neighbors, Gaussian mixture models, discriminant analysis, and logistic regression) began to be widely adopted in EEG research in the early stages. However, advanced techniques such as machine learning and deep learning techniques (e.g., extreme learning machine, neural network, Bayesian neural network, genetic programming, fuzzy set, long short-term memory, CNNs, ANNs, deep neural network, and asymmetric deep learning) received popularity in later periods. The specific evolution of techniques used in each topic can be seen in Fig. 12. For brevity, we only discuss a single technology-driven topic: *sleep and sleep quality*. In 2010, the most popular techniques were primarily *k*-means clustering, decision trees, and automated pattern recognition. In roughly 2013, techniques such as discriminant classification became popular. Later, the significance of k-nearest neighbors and ANNs was demonstrated. In 2015, the significant role of feature selection, nonlinear dynamical analysis, and Markov chains was highlighted. In the following two years, increasing numbers of AI techniques were involved, for example, classification, SVMs, and neural network. Most recently, there has been a dramatic increase in the number of advanced AI techniques, for example, machine learning, deep learning, CNNs, and neuro-fuzzy classifiers.

4.5 Publicly available datasets and software packages concerning EEG data analysis

We also summarize the datasets and software packages used in AI-enhanced EEG analysis studies by examining the full texts of the top 100 articles ranked by the number of annual citations (*C*/*Y*). The results are shown in Tables 9 and 10.

Based on the publicly available datasets, the results in Table 9 show that the dataset provided by University of Bonn [148] was the most commonly adopted in the top 100 studies. This dataset is composed of five subsets (A to E), each involving 100 one-channel instances. Subsets A and B are composed of EEG signals recorded from five healthy people in an awake state with their eyes open (A) and closed (B). Subsets C, D, and E were recorded from five patients. Subset D was recorded from the epileptogenic zone. Subset C was recorded from the hippocampal formation of the opposite hemisphere of the brain. Subsets C and D are composed of EEG signals recorded during seizure-free intervals (interictal). Subset E was recorded during seizure activity (ictal). This dataset had been popularly used in epileptic diagnosis and research (e.g., [50, 149, 150]).

BCI Competition[5] datasets were also popularly adopted in EEG studies. BCI Competition aims at validating BCIs signal processing and classification algorithms. Looking at Table 9, it can be seen that datasets provided by BCI Competitions III and IV were commonly adopted. For example, Zhang et al. [151] used the BCI Competition III dataset IVa and BCI Competition IV dataset IIb to verify the performance of their multi-kernel extreme learning machine method concerning EEG classification in BCIs. In the study by Zhang et al. [152], BCI Competition IV dataset IIb was used to demonstrate the performance of sparse Bayesian learning of frequency bands from EEGs for motor imagery classification.

There were also other open datasets available. For example, in terms of emotion analysis, there were two widely used datasets: DEAP [153] and MAHNOB HCI [154]. DEAP contains the EEGs and peripheral

[5] http://www.bbci.de/competition/.

Table 9 Commonly used datasets in AI-enhanced EEG studies

References	Major issue	Dataset	Reference/link
Kaya et al. [174]	Epileptic EEG signal classification	Data described by Andrzejak et al. [148]	[148]
Gandhi et al. [73]	EEG signal classification	Data described by Andrzejak et al. [148]	[148]
Şen et al. [80]	Sleep stage classification	Provided by St. Vincent's University Hospital and University College Dublin	[175]
Bhattacharyya and Pachori [176]	Patient-specific EEG seizure detection	Long duration EEG signal records from PhysioNet CHB-MIT scalp EEG database	[175, 177]
Sharma et al. [178]	Characterizing epileptic seizures	Data described by Andrzejak et al. [148]	[148]
Bhattacharyya et al. [179]	Automated detection of focal EEG signals	Bern-Barcelona EEG database	[156]
Suk and Lee [180]	Discriminative feature extraction in BCIs	The Technische University Berlin Dataset, BCI Competition III Dataset-IVa, and BCI Competition IV Dataset-IIa	https://wiki.ml.tu-berlin.de/wiki/Main/SS09_AnalysisOfNeuronalData [156, 181]
Tomioka and Müller [182]	EEG signal analysis	P300 dataset (dataset II) and Dean Krusienski in the BCI competition III	[183]
	EEG signal analysis	Dataset IV, BCI competition 2003	[184]
Sharma et al. [185]	Automated detection of focal EEG signals	Bern-Barcelona EEG database	[156]
Sharma et al. [186]	Focal EEG signal identification	Bern-Barcelona EEG database	[156]
Zhu et al. [187]	Sleep stage classification	Sleep-EDF dataset	[175]
Martis et al. [188]	Automated epilepsy detection	Bonn University open source database	http://epileptologie-bonn.de/cms/frontcontent.php?idcat=193
Sharma et al. [51]	Focal EEG signal identification	Bern-Barcelona EEG database	[156]
Acharya et al. [189]	Epileptic EEG signal classification	Data described by Andrzejak et al. [148]	[148]
Tiwari et al. [190]	Automated epilepsy diagnosis	Bern-Barcelona EEG database	[156]
Acharya et al. [49]	Automated epilepsy diagnosis	Bern-Barcelona EEG database	[156]
Guo et al. [191]	Automated epilepsy diagnosis	Data described by Andrzejak et al. [148]	[148]
Song et al. [192]	Automated epilepsy diagnosis	Bern-Barcelona EEG database	[156]
Hassan and Subasi [193]	Automated epilepsy diagnosis	Data described by Andrzejak et al. [148]	[148]
Hassan and Bhuiyan [194]	Automatic sleep scoring	Data described by Andrzejak et al. [148]	[148]
Sharma and Pachori [50]	Epileptic EEG signal classification	Data described by Andrzejak et al. [148]	[148]
Arunkumar et al. [195]	Classification of focal and non-focal EEG	Bern-Barcelona EEG database	[156]
Joshi et al. [149]	Classification of ictal and seizure-free EEG signals	Data described by Andrzejak et al. [148]	[148]
Bajaj and Pachori [196]	Seizure classification	Data described by Andrzejak et al. [148]	[148]
Fu et al. [197]	Seizure classification	Data described by Andrzejak et al. [148]	[148]

Table 9 (continued)

References	Major issue	Dataset	Reference/link
Zhang et al. [198]	Compressed sensing of EEG	A common dataset ('eeglab data.set') in the EEGLab	[173]
	Compressed sensing of EEG	Dataset in previous study	[199]
Cecotti and Graser [200]	EEG-based BCIs	Data set II from the third BCI competition	[183]
Schirrmeister et al. [53]	EEG decoding and visualization	BCI competition IV dataset 2a	[201]
Alam and Bhuiyan [202]	Detection of seizure and epilepsy	Database consists of 500 EEG segments and is available online	http://epileptologie-bonn.de/cms/front_content.php?idcat=193&lang=3&changelang=3
Chai et al. [203]	Driver fatigue classification	Dataset from a previous experimental study	[155, 204]
Riaz et al. [205]	EEG signals classification	Publicly available EEG dataset	http://epileptologie-bonn.de/cms/front_content.php?idcat=193&lang3
Samiee et al. [206]	Epileptic seizure classification	Data described by Andrzejak et al. [148]	[148]
Kumar et al. [207]	Epileptic seizure detection	Five sets (denoted A–E) from University of Bonn, Germany	http://epileptologie-bonn.de/cms/front_content.php?idcat=193&lang=3&changelang=3
Guo et al. [208]	Epileptic seizure detection	Data described by Andrzejak et al. [148]	[148]
Bandarabadi et al. [209]	Epileptic seizure prediction	European Epilepsy database	[210]
Kumar et al. [150]	Epileptic seizure detection	Bern-Barcelona EEG database	[156]
Ang et al. [211]	EEG classification in BCIs	BCI Competition IV Dataset 2a and Dataset 2b	[212]
Atkinson and Campos [213]	BCI-based emotion recognition	DEAP (Dataset for Emotion Analysis using EEG, Physiological and Video Signals) dataset	[153]
	BCI-based emotion recognition	BCI Competition III dataset IVa	http://www.bbci.de/competition/iii/
Zhang et al. [151]	EEG classification in BCIs	BCI Competition IV dataset IIb	http://www.bbci.de/competition/iv/
Gao et al. [214]	Analysis of nonlinear EEG time series	Data described by Andrzejak et al. [148]	[148]
Ang et al. [215]	Single-trial EEG-based BCIs	BCI Competition IV datasets IIa and IIb	[216, 217]
Zhang et al. [218]	Motor-imagery based BCIs	BCI Competition III dataset IVa	http://www.bbci.de/competition/iii/
Arvaneh et al. [219]	EEG-based BCIs	BCI Competition IV datasets IIa and IIb	[216, 217]
Alickovic et al. [220]	Automated epileptic seizure detection and prediction	Freiburg (intracranial EEG)	NA
	Automated epileptic seizure detection and prediction	CHB-MIT database	http://physionet.org/physiobank/database/chbmit/
Park et al. [221]	Seizure prediction	Freiburg EEG database	https://epilepsy.uni-freiburg.de/freiburg-seizure-prediction-project/eeg-database
Zhang et al. [152]	Motor imagery classification	BCI Competition IV dataset IIb	http://www.bbci.de/competition/iv/
Vidaurre et al. [222]	EEG-based BCIs	Dataset recorded by the Tubingen and BBCI groups	[157, 158]

Table 9 (continued)

References	Major issue	Dataset	Reference/link
Gao et al. [52]	Epileptic EEG signal classification	Data described by Andrzejak et al. [148]	[148]
Rivet et al. [56]	EEG-based BCIs	BCI Competition 2003-P300 Speller dataset	[184]
Zheng and Lu [79]	EEG-based emotion recognition	MAHNOB HCI	[154]
	EEG-based emotion recognition	DEAP	[153]
		Self-developed publicly available dataset	http://bcmi.sjtu.edu.cn/seed/index.html

physiological signals of 32 volunteers watching 40 one-minute music videos, including participants' ratings of each video (arousal, valence, like/dislike, dominance, and familiarity). MAHNOB HCI contains the EEGs, physiological signals, eye gaze, audio, and facial expressions of 30 volunteers watching 20 emotional videos. The volunteers self-reported their emotions in terms of arousal, valence, dominance, predictability, and emotional words. Furthermore, an EEG emotional dataset was developed by Zheng and Lu [79], which was acquired from 15 subjects by using emotional movie clips to assist volunteers to stimulate their emotions.

Other datasets were also available, for example, the Technische University Berlin database, Long duration EEG signal records from PhysioNet [155], CHB-MIT scalp EEG database, Bern Barcelona database [156], EEG time series data [156] provided by Department of Epileptology University of Bonn, and the dataset recorded by the Tubingen and the BBCI groups [157, 158].

The results of the software packages/toolboxes used in the top 100 AI-enhanced EEG studies are summarized in Table 10. It was found that most software packages/toolboxes were used for training and testing SVM models, for example, the R package e1071 [159], WEKA machine learning toolbox [160], and Matlab Bioinformatics Toolbox. This again indicates the popularity of SVMs in AI-enhanced EEG research. Moreover, other packages/toolboxes were used for classifier training, for example, the Matlab software package and LibSVM toolbox [161]. Two packages/toolboxes were used particularly for dealing with optimization issues, namely the Matlab package fmincon based on the SQP algorithm [162, 163] and the Poblano Toolbox [164].

Packages/toolboxes were also used for conducting deep learning and statistical analysis. For example, the DBNToolbox Matlab code [165] can be used for realizing DBNs and Matlab software version 7.8.0 (R2009a) for conducting feed-forward BPNN. The statistical Pattern Recognition Toolbox for Matlab can be used for kernel Fisher discriminant analysis. Several packages/toolboxes were found to be used for coefficients and entropy calculation, for example, the RAIT Matlab toolbox [166], Wavelet Toolbox Version 3.0 [167], BioSig Toolbox [168], and the LORETA-KEY package [169]. Other types of packages/toolboxes were used, for example, the Cross Recurrence Plot toolbox, Matlab's Statistics Toolbox and Neural Network Toolbox, MarsBaR toolbox (Brett et al., 2002) [170], Tensor Toolbox [171], N-way Toolbox for Matlab version 3.10 [172], and EEGLAB toolbox [173].

4.6 Latest research concerning AI-enhanced EEG analysis

To explore the major issues concerning the community in the last two years (i.e., 2019 and 2020), we further collected articles concerning AI-enhanced EEG analysis using the search query "artificial intelligence" or "machine learning" or "deep learning" or "neural network" and "EEG" or "electroencephalogra*", with the following restrictions to ensure that the returned records were: (1) published from January 1, 2019 to May 26, 2020; (2) covered the subject entitled "neurosciences;" (3) written in English; (4) research articles; and (5) indexed in SCI or SSCI databases. In this way, 231 records were returned and the key phrases extracted from the titles and abstracts. The extracted key phrases and keywords defined by each of the articles were used to identify major issues as measured by frequency (the significant ones are listed in Table 11).

On the whole, the major issues identified in articles published in the last two years were similar to those from the previous few years. However, there are still several issues worth highlighting. First, from the algorithm perspective, most studies were concerned with classification issues in the field of EEG analysis (e.g., [230–234]), for example, human mental emotion classification [230], classification of forearm movement imagery [231], detection of acute pain signals [232], sleep stage classification [235], classification of individuals into a normal group and one with particular diseases [236], and classification of repeating stimuli as either old or new [237]. Furthermore, ensemble classifiers are more effective than a single strong learner [238]. Thus, it is suggested that scholars should

Table 10 Commonly used software packages in AI-enhanced EEG studies

References	Major issue	Software package/ ToolBox	Purpose	Reference/link
Kaya et al. [174]	Epileptic EEG signal classification	WEKA	To train classifiers	https://www.cs.waikato.ac.nz/ml/weka/
Sharma et al. [185]	Automatic detection of focal EEG signals	Wavelet Toolbox	To calculate average Shannon wavelet entropy	[167]
Zhu et al. [187]	Classification of sleep stages	R package e1071	To train SVM model	[159]
Ang et al. [215]	Epileptic EEG signal identification	CRP Matlab toolbox 53	To plot cross recurrence	http://www.agnld.uni-potsdam.de/~marwan/toolbox/
Tiwari et al. [190]	Automated epilepsy diagnosis	WEKA	To train SVM classifier with radial basis function kernel	[160]
Hassan and Bhuiyan [194]	Automatic sleep scoring	Matlab Statistics Toolbox and Neural Network Toolbox	To conduct experiments	https://www.mathworks.com/
Alam and Bhuiyan [202]	Seizure and epilepsy detection	Matlab	To train, validate, and test classifiers	http://www.mathworks.com/help/toolbox/nnet/nnet_product_page.html
Bosl et al. [223]	EEG-based autism spectrum disorder detection	NetStation	To check scalp impedances	https://www.netdania.com/
Lin et al. [48]	EEG-based emotion recognition	LIBSVM	To build SVM classifier and use the radial basis function kernel to nonlinearly map data onto a higher dimension space	http://www.csie.ntu.edu.tw/~cjlin/libsvm
Samiee et al. [206]	Epileptic seizure classification	RAIT Matlab toolbox	To calculate coefficients and expansions	http://www.ijatesorg/index.php/ijates/article/view/18
Kumar et al. [207]	Epileptic seizure detection	Matlab Bioinformatics Toolbox	To train SVM model	https://www.mathworks.com/products/bioinfo.html
Bandarabadi et al. [209]	Epileptic seizure prediction	LibSVM toolbox	To train classifiers	[161]
Kumar et al. [150]	Epileptic seizure detection	Matlab Bioinformatics Toolbox	To train SVM model	https://www.mathworks.com/products/bioinfo.html
		Matlab	To conduct feed-forward BPNN	https://www.mathworks.com/matlabcentral/answers/29245-cursor-basics-matlab-7-8-0-r2009a
Frank et al. [224]	EEG predictors	MarsBaR toolbox	To extract a mean time course from each ROI	[170]
de Haan et al. [225]	EEG-based Alzheimer's disease detection	SPSS 15.0 package	To conduct statistical analysis	https://www.ibm.com/analytics/spss-statistics-software

Table 10 (continued)

References	Major issue	Software package/ ToolBox	Purpose	Reference/link
Ang et al. [215]	EEG-based BCIs	BioSig Toolbox	To calculate kappa values and standard error	[168]
Arvaneh et al. [219]	EEG-based BCIs	Package fmincon in Matlab	To solve optimization problem	[162]
Yanagisawa et al. [106]	Real-time control of a prosthetic hand	Brain-decoder-toolbox	To conduct decoding	http://www.cns.atr.jp/dni/en/downloads/brain-decoder-toolbox
Acar et al. [226]	Scalable tensor factorizations	Tensor Toolbox	To conduct CANDECOMP/PARAFAC Weighted OPTimization	http://csmr.ca.sandia.gov/ ~ tgkolda/TensorToolbox/
		Poblano Toolbox	To conduct optimization	[164]
		N-way Toolbox for Matlab	To conduct expectation maximization alternating least squares	http://www.models.kvl.dk/source/nwaytoolbox/
		Statistics Toolbox of Matlab	To generate box plots	NA
Park et al. [221]	Seizure prediction	Statistical Pattern Recognition Toolbox for Matlab	To conduct kernel Fisher discriminant analysis	http://cmp.felk.c-vut.cz/cmp/software/stprtool/)
Ahmadlou M and Adeli [227]	EEG-based ADHD diagnosis	MR system manufacturer's software package	Curve fitting and measurement of peak integrals	NA
		LORETA-KEY package	To calculate an average cross-spectral matrix for each subject in each EEG frequency band	[169]
		EEGLAB toolbox	To ensure that the EGG recordings were not contaminated with EMG and EOG artifacts	[173]
Zheng and Lu [79]	EEG-based emotion recognition	DBNToolbox Matlab code	To conduct deep belief networks	[165]
Guo et al. [228]	Epileptic EEG classification	GPLab software	To realize termination criteria	[229]

devote more effort to the integration of ensemble classifiers when addressing issues concerning AI-enhanced EEG analysis.

Second, machine learning and deep learning have been widely applied to EEG data analysis, particularly CNNs (e.g., [239–245]). CNNs are effective as function approximators and are commonly used to resolve classification issues involving EEG signal decoding for BCIs. Comparatively, an ANN's inside procedures can be much more difficult to be interpreted due to the thousands of parameters in the black boxes [246]. Hence, we can see that application of ANNs is relatively limited in the analysis of EEG data compared to CNNs. The application of CNNs in EEG studies includes intuitive robotic arm control [239], decode motor preparation of upper limbs [240], identity recognition [241], emotion recognition [242], decoding human brain activity [243], EEG motor imagery classification [244], and decoding EEG four-class motor imagery tasks [245].

Third, issues concerning feature extraction and selection were increasingly of concern to scholars (e.g., [247–253]). Recently, combining EEG signal feature extraction and classification methods have been widely used to identify mild cognitive impairments [254], driving fatigue state [250], and familiar and unfamiliar persons [252]. Although deep learning is effective for feature extraction, existing deep learning approaches typically require manual definition of sizable parameters. However, recent studies had proven the effectiveness of using hierarchical extreme learning machines, which require less manual intervention and extract features much faster than traditional deep learning algorithms [255]. In addition, feature selection is an important yet challenging issue, since there are numerous features, a small amount of clinical data exists, and there are many similarities between selected features. Recent studies have applied techniques such as Rényi min-entropy-based feature selection [249], common spatial

Table 11 Key phrases used in articles concerning AI-enhanced EEG analysis published in 2019 and 2020

Category	Key phrases	Frequency	Proportion (%)
Algorithms	Neural network	143	61.90
	Machine learning	77	33.33
	Classification	69	29.87
	Deep learning	42	18.18
	Convolutional neural network	44	19.05
	Support vector machine	23	9.96
	Artificial neural network	13	5.63
	Independent component analysis	10	4.33
	Logistic regression	10	4.33
	Random forest	9	3.90
	Short-term memory network	9	3.90
	Discriminant analysis	7	3.03
	k-nearest neighbor	7	3.03
	Graph theory	6	2.60
	Mouse model	6	2.60
Tools	EEG signal	45	19.48
	Functional connectivity	34	14.72
	Event-related potential	26	11.26
	MEG	28	12.12
	FMRI	10	4.33
	Magnetic resonance imaging	7	3.03
Feature	Feature extraction	17	7.36
	Feature selection	9	3.90
Applications	BCI	37	16.02
	Working memory	17	7.36
	Healthy control	16	6.93
	Attention	15	6.49
	Motor imagery	11	4.76
	Biomarker	9	3.90
	Sleep	8	3.46
	Signal processing	7	3.03
	Decision making	6	2.60
	Neurofeedback	5	2.16
Disorders	Epilepsy	21	9.09
	Alzheimer’s disease	15	6.49
	Cognitive impairment	12	5.19
	Synchronization	12	5.19
	ADHD	11	4.76
	Dementia	10	4.33
	Epileptic seizure	10	4.33
	Mild cognitive impairment	10	4.33
	Seizure detection	10	4.33
	Schizophrenia	9	3.90
	Neurological disorder	6	2.60
	Psychiatric disease	5	2.16
	Traumatic brain injury	5	2.16

pattern-based feature selection [251], and principal component analysis-based feature selection [253].

From an application perspective, several issues are of note. BCIs were found to be extensively popular for employing EEG signals to control devices with different applications (e.g., [256–264]). EEG-based BCIs in motor imagery have recently become prevalent [265]. However, in spite of the significant effectiveness, successful implementation of deep learning, particularly for inter-subject classification in cognitive BCIs, has only been recently proven [266]. Additionally, several recent studies particularly focused on issues concerning working memory, for example, the development of BCIs capable of continuously monitoring real-time working memory load [267], the exploration of the relationship between working memory task-associated EEG markers with fluid intelligence [268], and the study of uni- and bi-modal access to sensory working memory [269].

Issues regarding mental disorders are still of interest to scholars (e.g., [270–277]), in particular, epilepsy, Alzheimer's disease, mild cognitive impairments, synchronization, and attention-deficit/hyperactivity disorders. For epilepsy, recent research is concerned with issues such as proposing a deep learning–driven EEG approach to detect epileptic seizures from EEG discharges [278], epilepsy lateralization through intra-hemispheric brain networks based on resting-state magnetoencephalography data [279], and EEG-based multiclass seizure type classification using CNNs and transfer learning [280]. For Alzheimer's disease, recent studies have been concerned about issues such as classification of Alzheimer's disease [272, 274, 281], EEG microstate complexity for early diagnosis of Alzheimer's disease [277], and functional integration and segregation in multiplex brain networks for Alzheimer's disease [282].

5 Conclusion

By examining 2053 research articles about AI-enhanced human EEG analysis research, this study used bibliometrics, the word cloud technique, and STM methods to reveal a continuingly increasing interest in the research field. Analyses of articles and citations indicated a promising future for AI-enhanced human EEG analysis research. When examining the major research topics and their popularity across several periods, the word cloud analysis showed rich and vibrant activities in AI-enhanced human EEG analysis research in nearly all aspects.

Our study provides insights for scholars and policymakers seeking to better understand AI-enhanced human EEG analysis research. In general, as a crucial and emergent field, it is necessary to broaden the scope to thoroughly understand how AI can enhance human EEG analysis research and how human EEG analysis research can stimulate the innovation of AI technologies. The understanding of such a complex interdisciplinary research field will be enhanced through more studies. Although this study attempts to clarify such complexity, further scientific work is needed to fill the research gaps through more in-depth analysis

AI-enhanced human EEG analysis research has attracted an increasing level of attention since 2009. At the same time, the application of AI into human EEG analysis research has been ubiquitous and extremely popular, while AI-related technologies, specifically classification and SVM algorithms, have played an essential role. Similarly, although appearing later, machine learning algorithms have gradually received an increasing amount of attention. Moreover, human EEG research provides rich sources of inspiration for novel AI algorithms, which, in turn, advance the methodology of human brain research. For instance, the neural network algorithm was inspired by the architecture of neurons in the brain.

The results of the topic modeling and evolution analyses highlight the issues that have attracted a great deal of attention, including *epileptic seizure detection*, *brain–machine interface*, *EEG classification*, *mental disorders*, and *emotion*. There were also several topics that received increasing interest from academia in recent years, such as *alcoholism and anesthesia*, *emotion*, *epilepsy*, *fatigue driving*, and *sleep and sleep quality*.

The results from such bibliometric and visualization analyses will contribute to the advancement of research in this field in several ways, including assessing research progress, determining the most popular publication sources, distinguishing major scientific authors and institutions, identifying emerging research interests, and predicting future research directions.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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