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A Structural Topic Modeling-Based Bibliometric Study of Sentiment Analysis Literature

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Abstract

Sentiment analysis is an increasingly evolving field of research in computer science. With the considerable number of studies on innovative sentiment analysis available, it is worth the effort to present a review to understand the research on sentiment analysis comprehensively. This study aimed to investigate issues involved in sentiment analysis; for instance, (1) What types of research topics had been covered in sentiment analysis research? (2) How did the research topics evolve with time? (3) What were the topic distributions for major contributors? (4) How did major contributors collaborate in sentiment analysis research? Based on articles retrieved from the Web of Science, this study presented a bibliometric review of sentiment analysis with the basis of a structural topic modeling method to obtain an extensive overview of the research field. We also utilized methods such as regression analysis, geographic visualization, social network analysis, and the Mann–Kendal trend test. Sentiment analysis research had, overall, received a growing interest in academia. In addition, institutions and authors within the same countries/regions were liable to collaborate closely. Highly discussed topics were *sentiment lexicons and knowledge bases*, *aspect-based sentiment analysis*, and *social network analysis*. Several current and potential future directions, such as *deep learning for natural language processing*, *web services*, *recommender systems and personalization*, and *education and social issues*, were revealed. The findings provided a thorough understanding of the trends and topics regarding sentiment analysis, which could help in efficiently monitoring future research works and projects. Through this study, we proposed a framework for conducting a comprehensive bibliometric analysis.

Keywords Sentiment analysis · Bibliometric · Structural topic modeling · Social network analysis

Introduction

Predicting sentiments and emotions from people's texts is an essential concern in cognitive computing. The research on sentiment analysis has received increasing interest and attention from academia. With the wide ranges of scientific literature concerning sentiment analysis, it is significant and necessary to examine its trends and status, particularly the major research issues concerned by scholars. By using bibliometric analysis and structural topic modeling (STM), this study aimed to investigate sentiment analysis literature comprehensively. The remainder of this section is structured as follows: first, introducing the sentiment analysis; next, discussing cognitively inspired links/basis of sentiment analysis; third, introducing the bibliometric analysis of sentiment analysis research; and finally, discussing the research aims and questions of this study.

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Introduction to Sentiment Analysis

Sentiment analysis or opinion mining refers to the process and analysis of one's opinion, sentiment, and attitude toward an entity that is usually expressed in written texts [1]. Accordingly, with the prosperous studies and research outcomes that are constantly available in academia, sentiment analysis has become an active field within information processing. Considerable work concerning sentiment analysis has been conducted, of which, some of the latest studies are worth mentioning. For example, Ma et al. [2] presented a knowledge-rich approach to targeted aspect-based sentiment analysis, emphasizing on the leverage of commonsense knowledge within the deep neural sequential model. Specifically, they contributed to the field of sentiment analysis in three aspects. First, they proposed a two-step attention approach by attending to the words of the target expression, followed by the entire sentence. Second, they extended the classic long short-term memory (LSTM) cell with external knowledge. In addition, they incorporated the extended LSTM into deep neural networks (DNNs) with affective commonsense knowledge for sequence modeling. Agt-Rickauer et al. [3] described a method that supported domain modeling through formalized knowledge sources and information extraction from text. With an enormous number of innovative and promising sentiment analysis studies, it is worth the effort to conduct a thorough review to understand the proceedings in this field, as well as the scope for future research. In addition, there are some sophisticated and detailed reviews or surveys of the topic (e.g., [4–6]), among which the representative ones are summarized in Table 1. To the best of our knowledge, most of the abovementioned reviews were conducted using meta-analyses or manual-coding methods; therefore, there is a lack of quantitative assessment for larger-scale data.

Cognitively Inspired Links/Basis of Sentiment Analysis

Human emotions involve a wide range of complex characteristics regarding behavior, cognition, psychology, and physiology, and the analysis of human sentiments has become an essential issue in cognitive computing. Recently, the important role of cognitively inspired mechanisms is highlighted for enabling algorithms to be more intelligent and effective in extracting insightful knowledge from large-scale heterogeneous datasets [9]. Natural language processing (NLP) is closely related to various areas in cognitive science involving sentiment analysis. Scholars have claimed that NLP must be supplemented by cognitive and social perspectives to facilitate sentiment analysis, for example, subtle linguistic forms within opinions and simultaneous expressions of positive and negative nuances [10]. Typically, to train NLP applications, such as sentiment analysis systems, a large amount of labeled data is a necessity. However, manual annotation is a labor-intensive and expensive task. Hence, researchers are seeking ways to extract aspects directly from physiological activity data recorded when people are reading [11]. In addition, cognitive features have been proved effective in empowering sentiment analyzers to handle complex constructs, [12], indicating that cognitive analysis is a necessity for the development of sentiment analysis [13]. Many studies have proved the effectiveness of the integration of cognition-grounded data into NLP tasks [14]. Cognitive language processing data, such as eye-tracking features, have been proved to be effective for single NLP tasks [15], particularly for complex classification tasks such as sentiment analysis and sarcasm detection [16]. In the past decades, scholars of artificial intelligence had spent considerable effort on endowing machines with cognitive capabilities for the identification, interpretation, and expression of emotions and sentiments [10]. Xing et al. [17] presented a cognitive-inspired method for adapting a sentiment lexicon, a crucial tool for polarity classification and opinion mining, to a target domain using a significant amount of annotated data. By comparing the proposed cognition-based attention approach with several state-of-the-art sentiment analysis algorithms, Long et al. [14] demonstrated that the use of cognition-based eye-tracking data had advantages over other sentiment sources by considering information related to words and context.

Bibliometric Analysis of Sentiment Analysis Research

Bibliometric analysis has been considered and proven to be effective and reliable for evaluating scientific outputs, particularly in the era of "big data" through the use of mathematical and statistical methods [18]. In fact, according to our literature investigation, several bibliometrics-based reviews of sentiment analysis are available. For instance, Piryani et al. [19] conducted a scientometric analysis of 488 sentiment analysis studies between 2000 and 2016. They analyzed the data in terms of year-wise publication patterns, most prolific countries, institutions, publication sources and authors, scientific collaboration patterns, and topical density graphs and keyword bursts. Keramatfar and Amirkhani [20] presented a bibliometric analysis of sentiment analysis studies, focusing

Table 1 Summary of the recent reviews concerning sentiment analysis

Studies	Number of reviewed articles	Methods adopted	Research questions or aspects
Qazi et al. [7]	24	Meta-analysis	Types of opinions in online reviews, sentiment analysis tasks, and challenges addressed by machine learning and sentic computing approaches
Ravi and Ravi [4]	Around 100	Meta-analysis	Tasks, methodologies, and applications of sentiment analysis
Medhat et al. [8]	54	Meta-analysis	Categorization of recent sentiment analysis articles according to techniques
Hussein [5]	47	Meta-analysis	How sentiment analysis challenges affected sentiment evaluation

on factors such as discipline distribution, most influential authors and institutions, most cited documents, and keyword evolution. Their findings demonstrated that the term "sentiment analysis" was more accepted in comparison to "opinion mining." In addition, the support vector machine (SVM) was the most adopted approach for sentiment classification, and Twitter was the most adopted social network for sentiment analysis. Mäntylä et al. [21] conducted a computer-assisted literature review of 6996 sentiment analysis articles from Scopus by utilizing text mining and manual coding methods to, particularly, answer the question of "what research topics were investigated within sentiment analysis research." Ahlgren [22] explored answers to questions such as "who were the leading researchers." The major methods adopted included keyword analysis and latent Dirichlet allocation (LDA) modeling. Nevertheless, there are still some issues that have not been considered in the abovementioned reviews. First, in the previous bibliometrics-based reviews, the analysis data were initially retrieved data with no further manual filtering. The datasets might contain some noised records that were not well-related to the research target. Thus, the results obtained based on these records might not satisfactorily uncover the areas of interest. Second, even though Piryani et al. [19] conducted a manual data-cleaning process, they included all types of documents in the analysis, including reviews, editorial materials, and book reviews, most of which provided fewer original findings in comparison to the research articles and conference papers. Third, most of the up-to-date articles published after 2016 were not included in previous reviews. However, sentiment analysis research has been increasingly flourishing, particularly during the recent few years. Thus, the latest studies must be considered. Moreover, in studies that employed manual-coding methods, subjective judgment tended to affect the results. Thus, the findings might not be reliable or persuasive in comparison to those conducted using objective methods such as an innovative STM.

Research Aims and Questions

With the use of bibliometric analysis and STM, this study aimed to investigate the global sentiment analysis literature comprehensively. This study specifically sought to answer the following questions:

RQ 1: What were the article and citation trends in sentiment analysis research?
RQ 2: What research topics were covered by sentiment analysis research?
RQ 3: What would be the potential directions for future research?
RQ 4: What were the topical distributions for countries/regions, institutions, and authors?
RQ 5: What were the primary publication sources, as well as major contributors in sentiment analysis research?
RQ 6: What were the scientific collaborations between major contributors in sentiment analysis research?

The rest of this paper is structured as follows. A literature review is presented in the second major section. The third major section depicts the dataset and methodology, followed by the results of topic modeling analysis and performance analysis in the fourth and fifth major sections, respectively. The discussions and main conclusions are elaborated in the sixth and seventh major sections, respectively.

Literature Review

Research on Sentiment Analysis

As one of the most active fields in text classification, sentiment analysis focuses on extracting sentiment terms, such as aspects and opinions, and deciding their semantic orientations [23]. Sentiment analysis, as well as multi-attribute decision-making, has been widely researched recently to promote the decision-making process of the decision-makers [24]. Studies on sentiment analysis have introduced various techniques and tools for explicit and implicit aspect extractions [23]. Thus, sentiment analysis has gradually become an important research field, with the combination of the NLP and text mining techniques, to automatically detect and analyze the opinions or emotions hidden in documents. However, there are many practical challenges in sentiment analysis. For example, due to the expansion of social media types and usage, users are enabled to express their opinions through various domains [25–29] freely. Capturing these opinions can be costly because data from different domains must be annotated before being used for model training. Such a challenge prevents the exploration of large amounts of information being shared across domains [30]. Thus, sentiments must be extracted automatically from a variety of sources that are diverse, complex, and growing in volume. Table 2 presents a summary of some recent sentiment analysis studies. Given the availability of a large number of sentiment analysis literature (e.g., [42, 43]), it is important and essential to conduct a thorough review to understand its status and trends.

There are several reviews on sentiment analysis and its relevant topics (e.g., opinion mining and sentiment classification), integrating its research status and describing its development trends. For example, Ravi and Ravi [4] conducted a survey covering the sentiment analysis literature published between 2002 and 2015. Their study was organized by the subtasks of sentiment analysis, involving the utilized machine learning and NLP techniques, as well as sentiment analysis applications. Kumar and Sebastian [44] presented an

Table 2 Summary of recent sentiment analysis studies

Study	Year	Research focus	Level	Algorithms	Features
Kang et al. [31]	2018	Sentiment analysis	Document	Hidden Markov model and latent semantic analysis	Utilizing word orders without sentiment lexicons
Calefato et al. [32]	2018	Sentiment polarity detection	Document	Lexicon-based, keyword-based, and semantic features	Solving the problem of misclassifying neutral sentences as negative
Li et al. [33]	2018	Category text generation	Sentence	Reinforcement learning, generative adversarial networks, and recurrent neural networks (RNNs)	Generating category sentences to expand the original dataset and help in enhancing the generalization ability
Zhang et al. [34]	2018	Textual sentiment analysis	Document	Convolutional neural networks (CNNs), semantic, sentiment, and lexicon embeddings, LSTM, and attentive pooling	Extracting the global features of sentences and capturing hand-crafted and context information
García-Pablos et al. [35]	2018	Aspect and sentiment classification	Document	Guided topic modeling and continuous word embeddings	No need for supervision and domain- or language-specific resources
Zhao et al. [36]	2018	Twitter sentiment analysis	Document	CNNs, word embeddings, and n-grams	Capturing contextual information with recurrent structure and creating text representation using CNNs
Hassan and Mahmood [37]	2018	Sentence classification	Sentence	CNNs and RNNs	Reducing loss of detailed, local information and capturing long-term dependencies
Arif et al. [38]	2018	Sentiment analysis and spam detection	Document	Learning classifier systems, TFIDF, and word n-grams	Representing classifier rules to deal with sparseness in feature vectors
Dashtipour et al. [39]	2019	Sentiment analysis	Sentence	Dependency grammar-based rules and DNNs	Combining deep learning and linguistic rules to optimize polarity detection
Zhang et al. [24]	2019	Sentiment analysis	Sentence	Hesitant fuzzy set	Based on hesitant fuzzy set and sentiment word framework
Bahassine et al. [40]	2020	Feature classification	Document	The chi-square feature selection algorithm	Improving chi-square with three traditional features selection metrics namely mutual information, information gain and Chi-square
Ma et al. [2]	2018	Sentiment analysis	Sentence	LSTM	Focusing on leveraging commonsense knowledge in a deep neural sequential model
Song et al. [41]	2019	Aspect-level sentiment analysis	Document	Sentiment lexicon embedding	Better representing sentiment word's semantic relationships than existing word embedding techniques without manually-annotated sentiment corpus

overview of sentiment analysis in terms of its basic terminology, tasks, and levels. In addition, they discussed the potential practical applications of sentiment analysis. Serrano-Guerrero [45] reviewed and compared the main functionalities of 15 free-access web services concerning sentiment analysis.

In addition, several scholars provided discussions on issues regarding sentiment analysis, along with insights into the development of this field. For example, Cambria et al. [46] argued that there were at least 15 NLP problems related to sentiment analysis that should be addressed to realize human-like performance. The 15 problems were classified into three types, involving semantics, syntax, and pragmatics. Existing relevant reviews provided a clear picture of the main tasks, techniques, application domains, and challenges in sentiment analysis research, as summarized in Fig. 1.

Tasks of Sentiment Analysis (1) Sentiment classification aims at determining the sentiment orientation toward an entity from the expression texts of a user. Hence, it primarily focuses on classifying opinions into positive, negative, or neutral [45]. Studies concerning social emotion classification are widely available [47–50]. (2) Subjectivity classification is mainly defined as the determination of whether a given sentence is subjective or not. Subjectivity can be expressed differently and at various text levels, depending on the types of expressions. Thus, subjectivity classification is considered to be more complex than sentiment classification. (3) Opinion summarization involves extracting major features concerning a particular entity shared within documents, as well as the sentiments expressed toward them. (4) Review usefulness measurement and opinion

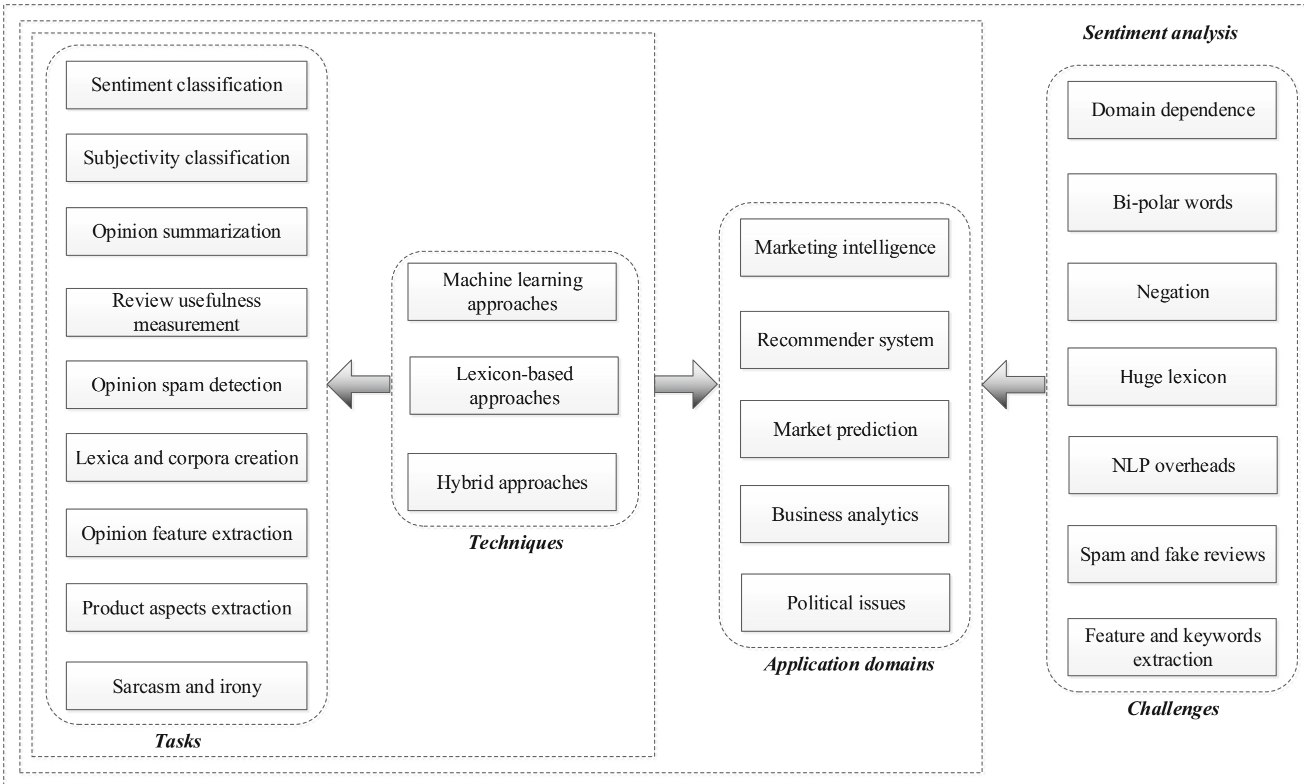

Fig. 1 Main tasks, techniques, application domains, and challenges in sentiment analysis research

spam detection have received significant attention because some market managers use fake reviews to promote their products or services. These two subtasks are different because review spam concerns itself more with good-quality reviews, while bad-quality reviews do not have to be review spam. (5) Lexica and corpora creation starts with seed words that are extended using their synonyms and antonyms collected from the WordNet dictionary [51]. (6) Opinion feature and product aspect extraction is related to the extraction of the most discussed and important aspects hidden within feedback texts. (7) Sarcasm and irony detection aims at identifying expressions involving irony and sarcasm. This subtask is complicated because scholars have not reached a consensus regarding the definitions of irony and sarcasm [52, 53].

Techniques Used in Sentiment Analysis Several scholars have attempted to examine the potential techniques for sentiment analysis. For instance, Medhat et al. [8] provided a refined classification of sentiment analysis techniques by using emotion detection and building resources, as well as transfer-learning. Machine learning involves both supervised and unsupervised techniques with the ability to select and extract an appropriate set of features in sentiment detection. Lexicon-grounded approaches depend primarily on sentiment lexicon. Hybrid approaches integrate both the supervised and unsupervised methods, as well as semi-supervised ones, which have been proven to be effective in sentiment classification [54].

Application Domains of Sentiment Analysis (1) Marketing intelligence aims to assist business managers in terms of opportunities and threat determination, competitor identification, competitors' actions preemption, and marketing decision-making. As indicated by Rambocas and Pacheco [55], the explosion of Internet-produced content along with innovative techniques such as sentiment analysis provides golden opportunities for marketers to promote market intelligence based on customer attitudes and brand opinions. (2) The performance of recommender systems can be enhanced by using sentiment analysis. For example, Contratres et al. [56] introduced a recommendation algorithm with the use of sentiment analysis to analyze textual datasets of Facebook and Twitter. The experimental results demonstrated that their approach could reduce cold-start issues. (3) Market prediction is another application area of sentiment analysis. Previous studies (e.g., [57–60]) have demonstrated the usefulness of sentiment analysis in market prediction. (4) Sentiment analysis has also been adopted by researchers in business analytics [61]. (5) Additionally, sentiment analysis is beneficial for political parties or governmental organizations because it helps them identify the public-satisfaction level with their policies and the chances of their winning in upcoming elections.

Challenges According to a survey by Hussein [5], major challenges regarding sentiment analysis included domain dependence, bipolar words, negation, huge lexicon, NLP overheads, spam and fake reviews, and feature and keyword extraction. Scholars have attempted to determine potential solutions to the above challenges. For example, a sentiment analysis system proposed by Kiritchenko et al. [62] was designed with the use of a supervised statistical text classification technique, which was used to detect the sentiments of short informal messages as well as those of a word or phrase within a message. Nandal et al. [63] proposed an innovative method for aspect-level sentiment detection with a particular focus on bipolar words. Jiménez-Zafra et al. [64] presented the first Spanish corpus annotated with negation for sentiment analysis. El Alaoui et al. [65] developed an innovative and adaptable method for sentiment analysis on large-scale social data. By comparing sentiment analysis on tweets with and without emoticons, Dandannavar et al. [66] aimed to determine whether emoticons could be used as reliable cues in sentiment analysis. Peng and Zhong [67] proposed three tasks to detect spam reviews, namely, generating a sentiment lexicon and computing the sentiment score by using a shallow dependency parser, establishing a set of discriminate rules, and detecting spam reviews by using a time series approach. Guzman and Maalej [68] aimed to automatically filter, aggregate, and analyze user reviews by detecting fine-grained app features with the use of NLP, extracting the user sentiments regarding the detected features, as well as clustering fine-grained features into higher-level features via topic modeling.

Applications of Bibliometric Analysis and STM

Bibliometric analysis, defined as the quantitative study of bibliographic data, is useful for evaluating large-scale literature data. The applications of bibliometric analysis have expanded drastically and rapidly in recent years, particularly due to the availability of computing power and an increasing number of easily accessible analytical tools [69]. Furthermore, bibliometric analysis has been widely implemented in various disciplines to depict the distribution patterns of scientific literature within a research field [70]. For example, by using both bibliometric analysis and word-cloud technique, Song et al. [71] identified and visualized the evolution of research themes concerning classroom dialogs. Martinho [72] studied 150 articles regarding the best management practices and agricultural economics by using bibliometrics and factor analysis. Jiang et al. [73] emphasized how bibliometric visualization could give new insights into the field of scientific literature by better communicating the major findings, enhancing data exploration, and presenting rich information. Pang and Zhang [74] presented the general cartography of green manufacturing literature to investigate its main ideas and issues by conducting a bibliometric analysis of 989 publications published between 1970 and 2018.

Bibliometric analysis is also popular for the research output assessment of interdisciplinary research fields [75–80]. For example, Chen et al. [81] performed a bibliometric analysis of the applications of NLP techniques for clinical trial text analysis by recognizing the predominant scholars and research issues and examining the research development. Chen et al. [82] presented a thorough picture of the *British Journal of Educational Technology (BJET)* to provide a comprehensive understanding of the development of the BJET in the past 50 years. They analyzed all volumes of the BJET publications in terms of publication and citation trends, distribution of publication types, major contributors, and predominant research issues. These research studies have presented solid evidence justifying that bibliometric analysis is powerful for mapping and evaluating the literature.

STM [83], a recent probabilistic extension to LDA, serves as a semi-automated machine learning approach to uncover hidden themes within a collection of documents [84]. Since its proposal, STM has been popular among scholars for exploring latent topics [85–90]. For example, with the use of open-ended survey items and STM, Rothschild et al. [91] sought to answer questions such as "what stereotypes did people hold regarding ordinary partisans?" To assess the attitudes of the residents with physical disabilities toward autonomous vehicles, Bennett et al. [84] analyzed the participants' responses by using STM. Chen et al. [92] studied the features, topics, and trends of the research concerning the human brain with the applications of artificial intelligence techniques by using STM.

Data and Methods

Data

The analytical framework used in this study for a comprehensive STM-based bibliometric analysis is illustrated in Fig. 2. We built our dataset using the Web of Science. As indicated by Liu [6], sentiment analysis became an active discipline since 2000. To ensure full coverage of the target articles, we set the time span from 1999 to 2018.

We used two types of strategies to retrieve data. The first strategy involved collecting publications that included proceedings papers or research articles with a research subject as "computer science." Articles containing keywords such as "sentiment analysis," "opinion mining," "sentiment classification," "opinion analysis," "semantic orientation," "opinion classification," or "sentiment mining," in titles, abstracts, or keywords were considered. The keywords were determined

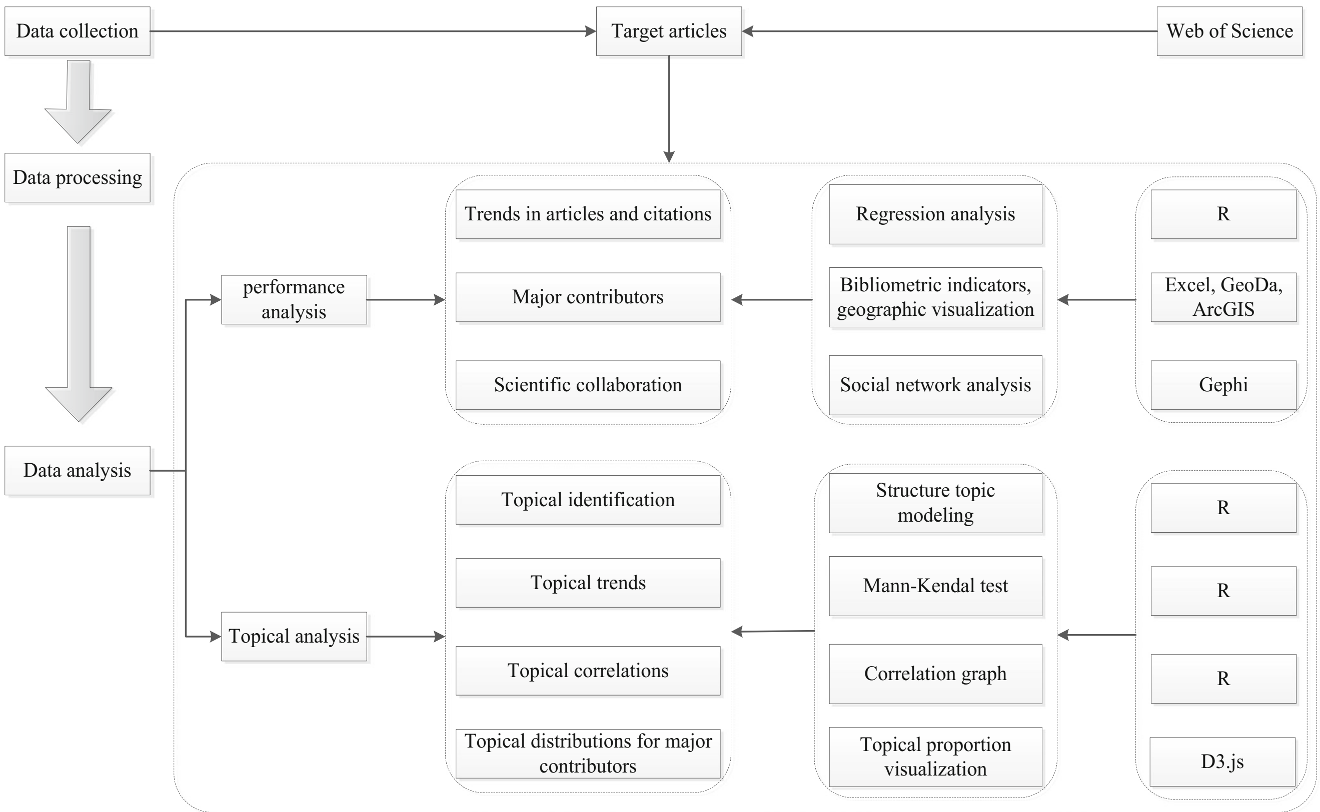

Fig. 2 Analytical framework of the study

and modified based on several previous studies, as summarized in Table 3. Accordingly, we obtained 5079 articles.

In addition, we adopted a second strategy as follows. We first used an extended list of search keywords, as presented in Table 4, to collect research articles written in English. The data was then restricted to those being indexed by the Science Citation Index and Social Science Citation Index databases because they are the most prestigious and offer robust resources for performing bibliometric analysis [74]. Accordingly, we obtained 7840 articles.

For the 12,919 articles[1] collected using the two strategies, we removed the duplicates and then conducted a filtering process based on the criteria listed in Table 5 to select the articles that were closely related to sentiment analysis. Two domain experts separately examined 200 articles, reaching interrater reliability of more than 95%. Next, they divided the rest of the articles into two groups, and each performed filtering on one of them. Four thousand three hundred forty-eight articles were selected as the final dataset. In addition, we included 25 articles of the IEEE Intelligent Systems on "Affective Computing and Sentiment Analysis" and collected their abstract information from the IEEE XPLORE database.[2] Thus, a total of 4373 articles were used for further data analysis.

Methods

To answer RQ1, we first computed the annual numbers of articles and citations, following which, we applied polynomial regression analysis using the *year* as an independent variable x. The coefficients of x^2 in the estimated regression model indicated an upward or downward trend of the distributions. A goodness-of-fit value R^2 indicated how well the estimated model fitted a set of observations. The estimated regression models could be used to predict future numbers of articles and citations.

To answer RQ2, we adopted the topic modeling method. Topic modeling extracts latent thematic structures within documents. STM [83, 93] is a newly proposed topic model to examine large-scale textual data and extract semantic information by using statistical algorithms. In this study, we utilized STM to uncover latent topics hidden in the sentiment analysis research. In STM, each article is assumed to be a mixture of multiple correlated topics, with representative terms and a prior distribution. The latent topics are estimated by considering each article as a mixture of correlated topics. Meanwhile, the article-level external covariates are combined with the prior distributions of article topics or topic words.

The generative steps for processing each article (indexed by d) with a vocabulary of size V in the STM with K topics are illustrated below.

[1] Available at: http://home.eduhk.hk/~hxie/data.zip
[2] https://ieeexplore.ieee.org/Xplore/home.jsp

Table 3 Keywords used in previous sentiment analysis reviews

Studies	Search keywords
Mäntylä et al. [21]	"Sentiment analysis," "opinion mining," "sentiment classification," "opinion analysis," "semantic orientation," "sentiwordnet," "opinion classification," "sentiment mining," "subjectivity analysis," "sentic," "subjectivity classification"
Keramatfar and Amirkhani [20]	"Opinion mining," "sentiment analysis"
Ahlgren [22]	"Sentiment analysis," "opinion mining," "sentiment classification," "polarity classification"
Piryani et al. [19]	"Sentiment analysis," "sentiment classification," "opinion mining," "opinion classification," "affect analysis," "affective computing," "sentiwordnet," "mining sentiments," "sentic," "mining sentiment"

(1) Based on a vector of article covariates X_d, as presented in Eq. (1), draw the article-level attention to each topic from a logistic-normal generalized linear model. In the equation, X_d denotes a p-by-1 vector, γ denotes a p-by-$(K-1)$ matrix of coefficients, and $\sum$ is a $(K-1)$-by-$(K-1)$ covariance matrix.

$$\overrightarrow{\theta}_d | X_{d\gamma}, \Sigma \sim \text{LogisticNormal}\left(\mu = X_{d\gamma}, \Sigma\right) \quad (1)$$

(2) Creating the article-specific distribution over terms on behalf of each topic k by baseline term distribution m, topic-specific deviation κ_k, covariate group deviation κ_g, and interaction between the two κ_i, as presented in Eq. (2). In the equation, m and κ_k, κ_g, and κ_i denote the V-length vectors including one entry per term in the vocabulary.

$$\beta_{d,k} \propto \exp\left(m + \kappa_k + \kappa_{gd} + \kappa_{i=(k,gd)}\right) \quad (2)$$

(3) For each term in the article ($n \in 1, \ldots, N_d$), first, draw the term's topic assignment, as presented in Eq. (3). Second, draw an observed word from a particular topic, as presented in Eq. (4).

$$z_{d,n} | \overrightarrow{\theta}_d \sim \text{Multinomial}\left(\overrightarrow{\theta}_d\right) \quad (3)$$

$$w_{d,n} | z_{d,n}, \beta_{d,k=z_{d,n}} \sim \text{Multinomial}\left(\beta_{d,k=z_{d,n}}\right) \quad (4)$$

We used STM to cluster our articles with the use of abstracts, titles, and keywords. We assigned weights (i.e., 0.4, 0.4, and 0.2) to the terms extracted from keywords, titles, and abstracts, respectively [79]. We also filtered unimportant terms by using term frequency-inverse document frequency [94]. We then applied the R package *stm* [83, 93] to perform the STM task. According to previous studies [95, 96], we executed different models with a set of topics (i.e., ranging from 15 to 42). Next, by reviewing the most discriminating terms and articles of each topic, we selected the model with the most semantics [97]. Thus, a 16-topic model was selected.

Furthermore, with a topic-term distribution matrix estimated by STM, we identified the representative terms for each topic. Topical labels were then assigned to each topic on the basis of a review of representative terms and articles by domain experts with prior knowledge of sentiment analysis.

For RQ3, a nonparametric Mann–Kendall (MK) trend test [98] was conducted to statistically examine the existence of a significant upward or downward trend for each topic. An upward (downward) trend indicated that research on the topic constantly increased (decreased) with time.

To answer RQ4, we visualized the topical proportion for each country/region, institution, and author. The basic topical distribution graph was constructed by using a cluster purity

Table 4 The extended list of keywords used for searching articles

"Sentiment lexicon," "sentiment embedding," "sentiment analysis," "opinion mining," "sentiment classification," "opinion analysis," "semantic orientation," "sentiwordnet," "opinion classification," "sentiment mining," "subjectivity analysis," "sentic," "subjectivity classification," "sentiment classification," "polarity classification," "social emotion," "emotion classification," "emotion detection," "affective computing," "affective resource," "affective data," "affective reasoning," "affective intuition," "affective space," "affective information," "affective knowledge," "affective analysis," "affective text," "opinion detection," "sentiment detection," "subjectivity detection," "polarity detection," "sentiment learning," "subjectivity learning," "affective learning," "sentiment identification," "opinion identification," "subjectivity identification," "polarity identification," "emotion identification," "affective identification," "emotional identification," "sentiment classifier," "opinion classifier," "subjectivity classifier," "sentiment classifier," "polarity classifier," "emotion classifier," "emotional classifier," "affective classifier," "sentiment categorization," "opinion categorization," "subjectivity categorization," "sentiment categorization," "polarity categorization," "emotion categorization," "emotional categorization," "affective categorization," "sentiment recognition," "opinion recognition," "subjectivity recognition," "sentiment recognition," "polarity recognition," "emotion recognition," "emotional recognition," "affective recognition"

Table 5 Examples of inclusion and exclusion criteria for data verification

Inclusion criteria	I1	Emotional polarity analysis
	I2	Predict election outcomes or market trends from sentiment
	I3	Public's opinion on particular issues or products
	I4	Emotional scoring
	I5	Semantic features extraction for sentiment analysis
	I6	Sentiment analysis for texts in social media
	...	...
Exclusion criteria	E1	Physical emotion detection and medical classification
	E2	Affective posture recognition
	E3	Human's emotion recognition ability
	E4	Articles of introduction, comment, and review types
	E5	Theory of mind
	E4	Cognitive neuroscience
	E7	Articles without abstract
	E8	Pure psychological experimental studies
	...	...

visualizer. Furthermore, we modified the graph by using JavaScript packages d3.v3.js[3] and clusterpurityChart.js.[4]

For the analyses of major countries/regions, institutions, and authors, we followed the method proposed by Song et al. [71, 99] to include all actors participating in each article. To answer RQ5, we calculated several bibliometric indicators for each country/region, institution, and author. We then ranked them on the basis of article count and Hirsch index (H-index) to identify the most prolific and influential ones, respectively. H-index indicates that H of one's articles have received at least H citations each [100]. It has been popularly adopted to assess one's academic performance from the perspectives of both quantity and quality [70].

To answer RQ6, we adopted social network analysis (SNA) to visualize the scientific collaborations between countries/regions, institutions, and authors. SNA is an exploration of social structures by adopting social network and graph theories, with nodes representing actors and links indicating relationships or interactions between them. In this study, we conducted SNA by using Gephi,[5] where the node size and link width indicated the article count and collaboration strength, respectively.

Topical Analysis Results

Trend Analysis of Articles and Citations

Figure 3 depicts the time evolution of the annual numbers of articles and citations, with the integration of polynomial regression results. The exponential growth in both the article and citation counts demonstrated an increase in interest and enthusiasm among authors toward sentiment analysis research.

According to Mäntylä et al. [21], approximately 99% of the articles related to sentiment analysis appeared after 2004, and the modern sentiment analysis began to be conducted intensively in the mid-2000s, with a particular focus on online product reviews. As indicated by Liu [101], sentiment analysis had experienced an increasing trend from the year 2002, and it had grown drastically to be one of the most active fields in data mining, NLP, and web mining. In this study, approximately 99% of the studied articles were published after 2007, and research on sentiment analysis had been increasing since then.

Topical Identification and Trend Analysis

The most frequently used terms in sentiment analysis research are listed in Table 6, with "review" (appears in 1369 articles, occupies 31.30%) being the most popular one, demonstrating that the sentiment analysis of reviews of products or services was a great concern among authors. Other frequently used terms were "network" (1039, 23.75%), "product" (945, 21.60%), and "emotion" (901, 20.60%). Table 7 presents the results of 16-topic STM. Among all the identified topics, the top five highly discussed topics were *sentiment lexicons and knowledge bases* (9.38%), *aspect-based sentiment analysis* (9.09%), *social network analysis* (8.79%), *multiple domains and cross-domain adaption* (8.43%), and *conventional machine learning and optimization methods* (7.40%).

The trend test results show that five topics, namely, *social network analysis*, *deep learning for natural language processing*, *web services*, *recommender systems and*

[3] https://d3js.org/d3.v3.js

[4] https://bl.ocks.org/nswamy14/raw/e28ec2c438e9e8bd302f/clusterpurityChart.js

[5] https://gephi.org/

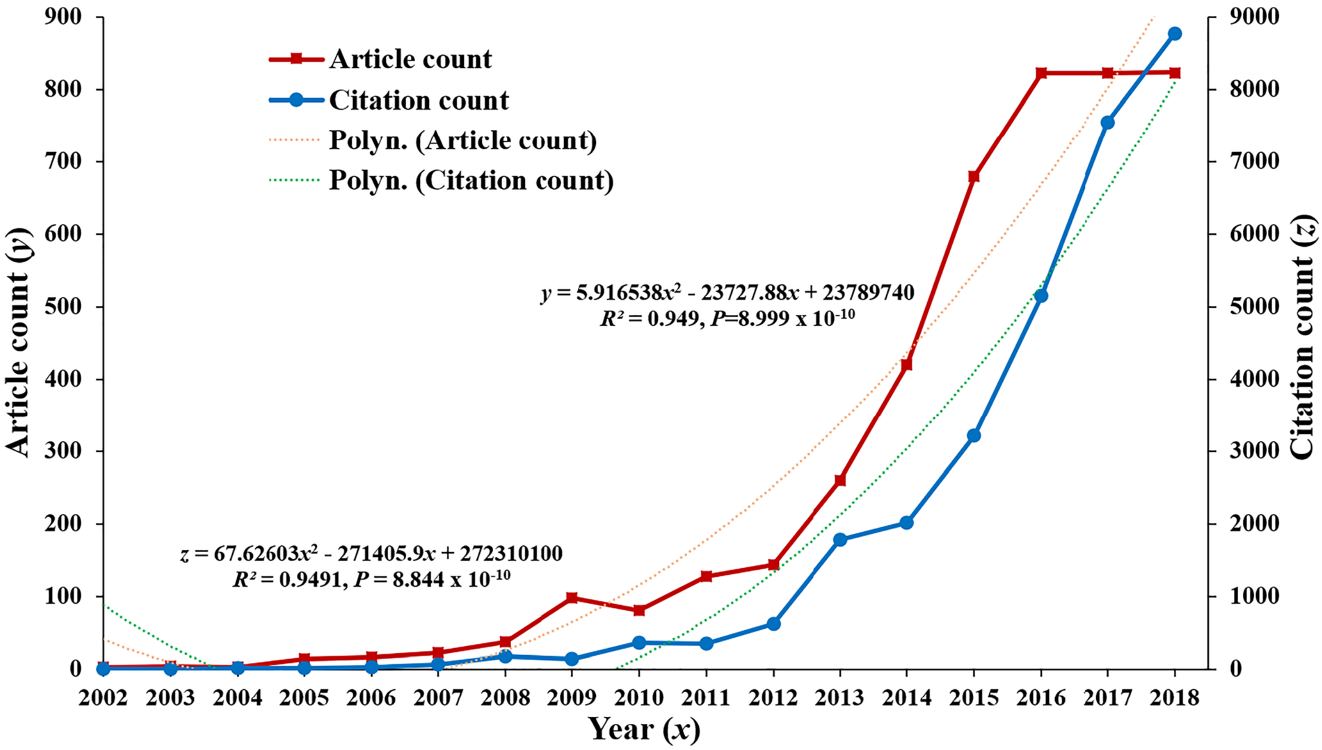

Fig. 3 Trend analysis of article and citation counts

Table 6 Top frequently used terms in sentiment analysis research

2002–2018			2002–2013			2014–2018		
Term	N	%	Term	N	%	Term	N	%
Review	1369	31.30	Review	310	38.41	Review	1059	29.70
Network	1039	23.75	Product	221	27.39	Network	930	26.08
Product	945	21.60	Topic	169	20.94	Twitter	806	22.60
Emotion	901	20.60	Extraction	165	20.45	Emotion	779	21.85
Twitter	895	20.46	Document	160	19.83	Product	724	20.30
Topic	827	18.91	Semantic	155	19.21	Tweet	685	19.21
Tweet	737	16.85	Sentence	153	18.96	Topic	658	18.45
Domain	659	15.07	Domain	129	15.99	Domain	530	14.86
Extraction	627	14.33	Emotion	122	15.12	Lexicon	485	13.60
Sentence	610	13.95	Orientation	115	14.25	Detection	483	13.54
Semantic	586	13.40	Customer	111	13.75	Extraction	462	12.96
Lexicon	580	13.26	Network	109	13.51	Sentence	457	12.82
Detection	570	13.03	Blog	103	12.76	Aspect	452	12.68
Aspect	522	11.93	Lexicon	95	11.77	Semantic	431	12.09
Document	522	11.93	Chinese	92	11.40	Public	421	11.81
Customer	492	11.25	Twitter	89	11.03	Neural	403	11.30
Public	484	11.07	Detection	87	10.78	Emotional	382	10.71
Emotional	441	10.08	Expression	83	10.29	Customer	381	10.68
Comment	428	9.79	Movie	82	10.16	Document	362	10.15
Neural	419	9.58	Linguistic	79	9.79	Comment	353	9.90

Table 7 STM analysis results with 16 identified topics

Discriminating terms	%	Suggested labels	Trend	p
Phrase, urdu, semantic, syntactic, orientation, dependency, rule, collocation, crf, sentence, parsing, relation, target, extraction, adjective	9.38	*Sentiment lexicons and knowledge bases*	↓↓	0.0235
Aspect-based, myanmar, aspect, product, review, absa, e-commerce, merchant, implicit, ate, ranking, aspect-opinion, aspect-level, explicit, feature-opinion	9.09	*Aspect-based sentiment analysis*	↑	0.9671
Fan, retweet, hashtag, tweet, twitter, soccer, leader, stream, trending, facebook, networking, bitcoin, football, sn, event	8.79	*Social network analysis*	↑↑↑↑	0.0001
Domain-specific, cross-lingual, malay, self-training, lexicon, multilingual, cross-domain, meta-level, disambiguation, supervision, emoticon, immune, semi-supervised, adaptation, domain, co-training	8.43	*Multiple domain and cross-domain adaption*	↑	0.7108
Naive, bayes, ensemble, k-nearest, swarm, particle, selection, weighting, multi-class, svm, preprocessing, indonesian, maximum, stopword, entropy, knn, tfidf, k-means	7.40	*Conventional machine learning and optimization methods*	↑	0.9016
Valence-arousal, va, gmm, circumplex, multi-label, time-frequency, music, expressivity, human-machine, temperature, eeg, affective, arousal, emotion, signal, emotinet	6.84	*Bio-signals and emotion models*	↓↓	0.0290
Deep, convolutional, cnn, lstm, recurrent, rnn, bidirectional, convolution, autoencoder, pre-trained, dbn, bilstm, gru	6.83	*Deep learning for natural language processing*	↑↑↑	0.0020
Ewom, mapreduce, big, tourist, cloud, saas, hadoop, spark, airline, disaster, sale, nuclear, intelligence, satisfaction	6.50	*Web services*	↑↑↑↑	0.0006
Dirichlet, lda, weibo, sentiment-topic, multi-feature, chinese, topic-sentiment, jst, multi-grain, latent, hot, topic, allocation, joint, sentimental	6.05	*Topic model*	↓	0.5923
Negation, sarcasm, spam, irony, fake, email, figurative, sarcastic, spammer, deceptive, ironic, detection, satire, satirical	5.46	*Spam and sarcasm detection*	↓	0.3031
Stock, financial, investor, trading, volatility, portfolio, trader, bankruptcy, price, news, guba, sp., forecasting, return	5.33	*Financial market*	↑	0.0638
Recommendation, recommender, app, star, helpfulness, cf., fuzzy, rating, mobile, filtering, collaborative, item, travel, recommend, explainable, uninorm	4.79	*Recommender systems and personalization*	↑↑	0.0151
Blogger, subtopic, ontology, image, flickr, extractive, retrieval, query, visualization, selfie, underground, visual, multimedia, retweeting, video	4.26	*Multimedia and multi-modality*	↑	0.8368
Stance, voter, echo, arguing, contentious, trump, political, donald, referendum, election, republican, presidential, nostalgia, clinton, parliamentary, electoral	3.93	*Political and media issues*	↑	0.1494
Health, student, drug, teaching, portuguese, cancer, surveillance, teacher, tobacco, forum, education, spanish, writing, educational, university	3.70	*Education and social issues*	↑↑	0.0120
Cognition, deficit, empathy, impairment, schizophrenia, cortex, oxytocin, parkinson, prefrontal, human-agent, epilepsy, amygdala, asd, injury, mdma	3.23	*Emotion-related disease*	↓	0.3031

Note: Topics are ranked by the proportion in descending order; %: topic proportions. Abbreviations of representative terms are shown in Table S1 in the Appendix. ↑(↓): topic showing an increase (decrease) in proportion annually but not significant ($p > 0.05$); ↑↑(↓↓), ↑↑↑(↓↓↓), ↑↑↑↑(↓↓↓↓): topic showing a significant increase (decrease) in proportion annually ($p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively)

personalization, and *education and social issues*, exhibited significantly increasing trends at the two-sided $p = 0.05$ level, whereas two topics, namely, *sentiment lexicons and knowledge bases* and *bio-signals and emotion models*, exhibited significantly decreasing trends. Figure 4 presents the annual trends of the topic proportions.

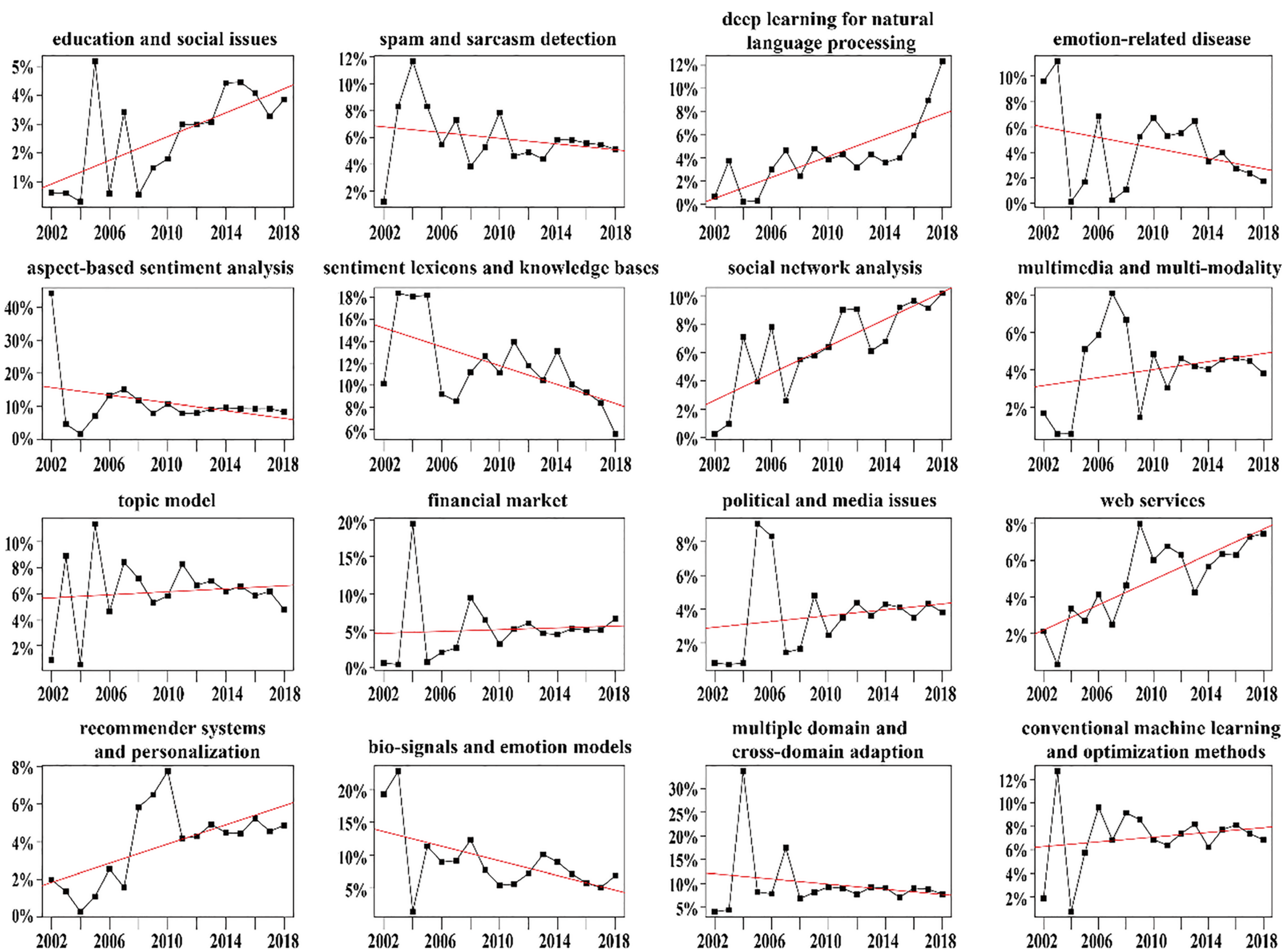

Fig. 4 Annual trends of the identified topics

Topical Distributions of Countries/Regions, Institutions, and Authors

We visualized the topical proportion distributions of the prolific countries/regions, institutions, and authors, as depicted in Fig. 5. From the country/region perspective, the USA was more active in conducting research on *sentiment lexicons and knowledge bases*, and Italy and Japan were productive in research on *aspect-based sentiment analysis*. South Korea showed more concern for research on *social network analysis.*

From an institution perspective, *National Institute of Technology* was more active in conducting research on *sentiment lexicons and knowledge bases*. *Harbin Institute of Technology* showed great interest in *social network analysis* and *sentiment lexicons and knowledge bases*. *University of Tokushima* was especially active in conducting research on *topic model* and *aspect-based sentiment analysis*. *Indian Institute of Technology* showed great concern about *deep learning for natural language processing*. From an author perspective, *Erik Cambria* and *Amir Hussain* were active in research on *sentiment lexicons and knowledge bases*. *Fuji Ren* and *Flavius Frasincar* were especially interested in *aspect-based sentiment analysis*. *Mike Thelwall*, *Ting Liu*, *Bing Qin*, and *Hua Xu* were especially active in research on *bio-signals and emotion models*. The authors having a high interest in *deep learning for natural language processing* included *Ting Liu*, *Bing Qin*, *Erik Cambria*, and *Soujanya Poria*.

Performance Analysis Results

Publication Sources Analysis

The most active source in publishing sentiment analysis studies was *Lecture Notes in Computer Science (LNCS)*, as shown in Table 8. The total number of articles published in *LNCS* was significantly larger than that in other book series, proceedings, or journals. This finding was consistent with the work by Keramatfar and Amirkhani [20]. *ACM International Conference Proceeding Series* was the second most prolific

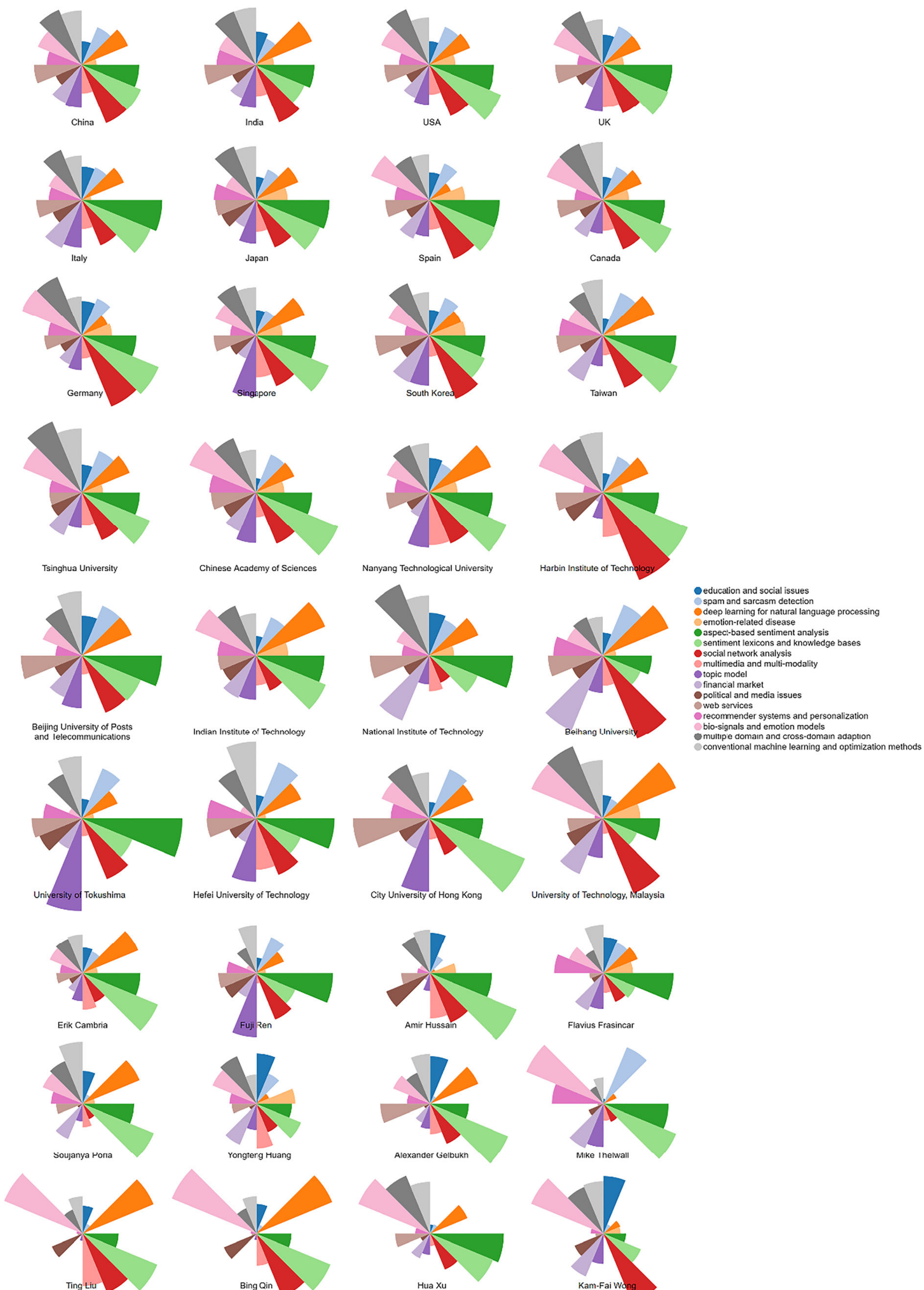

Fig. 5 Topical proportion distributions of the prolific countries/regions, institutions, and authors in sentiment analysis research

Table 8 Publication venues ranked by article count

Publication sources	Type	AC	H (R)	CC (R)	ACP	2002–2013		2014–2018		≥ 200	≥ 100	≥ 50	≥ 25	≥ 10
						AC (R)	CC (R)	AC (R)	CC (R)					
Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)	Proceedings	515	19 (3)	1747 (2)	3.39	141 (1)	199 (3)	374 (1)	1548 (2)	0	1	3	15	43
ACM International Conference Proceeding Series	Proceedings	231	16 (5)	1193 (7)	5.16	25 (4)	118 (9)	206 (2)	1075 (6)	0	2	5	9	31
Communications in Computer and Information Science	Proceedings	95	6 (23)	166 (32)	1.75	29 (2)	14 (27)	66 (4)	152 (32)	0	0	0	0	4
Advances in Intelligent Systems and Computing	Proceedings	78	6 (23)	89 (50)	1.14	5 (19)	2 (77)	73 (3)	87 (47)	0	0	0	0	0
Expert Systems with Applications	Journal	78	23 (1)	1932 (1)	24.77	27 (3)	171 (5)	51 (7)	1761 (1)	0	6	9	23	42
IEEE International Conference on Data Mining	Proceedings	68	10 (9)	334 (14)	4.91	20 (5)	11 (32)	48 (8)	323 (14)	0	0	1	3	10
Procedia Computer Science	Proceedings	63	7 (18)	272 (19)	4.32	4 (28)	0	59 (5)	272 (18)	0	0	1	2	6
Knowledge-Based Systems	Journal	61	20 (2)	1209 (6)	19.82	5 (19)	8 (37)	56 (6)	1201 (4)	0	3	7	16	30
Decision Support Systems	Journal	39	17 (4)	1101 (8)	28.23	13 (7)	77 (10)	26 (12)	1024 (7)	0	1	9	14	25
IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining	Proceedings	36	8 (16)	154 (34)	4.28	16 (6)	15 (26)	20 (16)	139 (34)	0	0	0	1	4
IEEE Access	Journal	33	6 (23)	80 (54)	2.42	0	0	33 (9)	80 (49)	0	0	0	0	2
Information Processing & Management	Journal	33	14 (6)	526 (12)	15.94	3 (36)	20 (23)	30 (10)	506 (11)	0	0	2	8	19
Front Artif Intel AP	Proceedings	29	3 (59)	32 (114)	1.1	5 (19)	2 (77)	24 (15)	30 (118)	0	0	0	0	0
Cognitive Computation	Journal	28	10 (9)	240 (23)	8.57	2 (57)	2 (77)	26 (12)	238 (20)	0	0	0	3	11
Neurocomputing	Journal	28	9 (12)	321 (15)	11.46	2 (57)	2 (77)	26 (12)	319 (15)	0	0	1	3	9
PLoS One	Journal	27	7 (18)	198 (27)	7.33	0	0	27 (11)	198 (22)	0	0	1	2	4
IEEE Intelligent Systems on "Affective Computing and Sentiment Analysis"	Journal	26	14 (6)	1023 (9)	39.35	11 (9)	53 (14)	15 (24)	875 (10)	1	1	7	12	17
International Conference on Advances in Computing, Communications and Informatics	Proceedings	26	4 (42)	37 (100)	1.42	6 (16)	0	20 (16)	37 (98)	0	0	0	0	0
IEEE Transactions on Affective Computing	Journal	23	12 (8)	299 (18)	13	7 (13)	18 (24)	16 (23)	281 (17)	0	0	1	3	13
International Conference on Asian Language Processing	Proceedings	22	2 (108)	17 (189)	0.77	3 (36)	0	19 (19)	17 (182)	0	0	0	0	0
Journal of Information Science	Journal	22	9 (12)	201 (24)	9.14	3 (36)	4 (55)	19 (19)	197 (23)	0	0	0	1	9

≥ 200, ≥ 100, ≥ 50, ≥ 25, and, ≥ 10: numbers of articles with more than 200, 100, 50, 25, and ten citations, respectively

R, ranking position; *H*, H-index; *AC*, total articles; *CC*, total citations; *ACP*, average citations per article source. Notably, most of the prolific sources were found to be proceedings, while most sources with a high H-index value were journals, as shown in Table 9. In addition, *Expert Systems with Applications* and *Knowledge-Based Systems* was the most influential sources in publishing sentiment analysis research. It was noteworthy that *IEEE Intelligent Systems on* "*Affective Computing and Sentiment Analysis*" was the 17th and sixth most prolific and influential publication source, respectively.

Country/Region Analysis

A total of 96 countries/regions participated in the publication of sentiment analysis research. The global heat map at the country/region level is depicted in Fig. 6. Furthermore, Tables 10 and 11 summarize the most prolific and influential countries/regions, respectively. From the results, China was very active in the research, with the most number of articles (1051), while the USA was the most influential country with an H-index of 41. However, the USA had significantly fewer articles than China. Such results showed a high quality of the sentiment analysis articles produced in the USA.

Institution Analysis

A total of 2493 institutions participated in publishing research associated with sentiment analysis. Tables 12 and 13 depict the most prolific and influential institutions, respectively. From the results, four of the top five productive institutions were from China, with *Tsinghua University* (90 articles) and *Chinese Academy of Sciences* (83 articles) being the top two. *Nanyang Technological University* ranked in the third place for productivity and the first place as the most influential institution in sentiment analysis research. Notably, the universities from Eastern and Southeast Asian countries/regions dominated the publication of sentiment analysis research (nine from China, two from Hong Kong, and one from Singapore).

Author Analysis

Tables 14 and 15 depict the most prolific and influential authors, respectively. From the results, the top three prolific authors were *Erik Cambria*, *Fuji Ren*, and *Amir Hussain*. *Erik Cambria* and *Amir Hussain* were also among the top three most influential authors.

Collaboration Analysis

The collaborations between 34 countries/regions with an article count ≥ 30 are visualized in Fig. 7, with 34 nodes and 207 links. Among the 34 countries/regions, 15 were from Asia, 13 from Europe, three from North America, one from South America, one from Oceania, and one from Africa. China and the USA were the closest collaborators (collaborating in 101 articles), followed by China and Hong Kong (58 articles), as well as China and Japan (36 articles).

The collaboration network of 33 institutions with an article count ≥ 20 is illustrated in Fig. 8, with 33 nodes and 64 links. Among the 33 institutions, 15 were from China, three from Hong Kong, three from India, and two from Singapore. The closest collaborative partners were *University of Tokushima* from Japan and *Hefei University of Technology* from China (collaborating in 19 articles), followed by *University of Chinese Academy of Sciences* and *Chinese Academy of Sciences* (15 articles), as well as *Nanyang Technological University* and *University of Stirling* (15 articles). The scientific collaborations among authors with an article count ≥ ten are presented in Fig. 9, with 38 nodes and 30 links. Among the 38 authors, 18 were from China, three from the Netherlands, and three from Singapore. The closest collaborative partners were *Soujanya Poria* from *Singapore University of Technology and Design* and *Erik Cambria* from *Nanyang Technological University* (16 articles), followed by *Fuji Ren* from the *University of Tokushima* (15 articles), as well as *Amir Hussain* (formerly) from the *University of Stirling* and *Erik Cambria* from *Nanyang Technological University* (15 articles).

Discussion and Conclusions

Performance Analysis

This study proposed an STM-based bibliometric analysis approach for evaluating 4373 articles related to sentiment analysis. The sentiment analysis research had received an overall growing interest in academia. Furthermore, citations received by these articles annually had experienced a significant increase. These findings provided an answer to RQ1.

Answers to RQ5 were indicated by the analyses of the publication sources, countries/regions, institutions, and authors. The publication sources analysis demonstrated the outstanding performance of *Lecture Notes in Computer Science* in publishing articles associated with sentiment analysis. Such a result was in accordance with the work by Mäntylä et al. [21]. The sentiment analysis studies published by *Expert Systems with Applications* were the most influential with the highest H-index value. China had made significant contributions to sentiment analysis research, with approximately 25% of the total studied articles, while the USA was the most influential country as measured by the H-index. Notably, *Tsinghua University* was the most prolific in publishing sentiment analysis research. The top five prolific institutions identified were consistent with the results obtained by Keramatfar and Amirkhani [20], namely, *Tsinghua University*, *Chinese Academy of Sciences*, *Nanyang Technological University*,

Table 9 Publication venues ranked by H

Publication sources	Type	H	AC (R)	CC (R)	ACP (R)	2002–2013		2014–2018		≥200	≥100	≥50	≥25	≥10
						AC (R)	CC (R)	AC (R)	CC (R)					
Expert Systems with Applications	Journal	23	78 (4)	1932 (1)	24.77	27 (3)	171 (5)	51 (7)	1761 (1)	0	6	9	23	42
Knowledge-Based Systems	Journal	20	61 (8)	1209 (6)	19.82	5 (19)	8 (37)	56 (6)	1201 (4)	0	3	7	16	30
Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)	Proceedings	19	515 (1)	1747 (2)	3.39	141 (1)	199 (3)	374 (1)	1548 (2)	0	1	3	15	43
Decision Support Systems	Journal	17	39 (9)	1101 (8)	28.23	13 (7)	77 (10)	26 (12)	1024 (7)	0	1	9	14	25
ACM International Conference Proceeding Series	Proceedings	16	231 (2)	1193 (7)	5.16	25 (4)	118 (9)	206 (2)	1075 (6)	0	2	5	9	31
IEEE Intelligent Systems on "Affective Computing and Sentiment Analysis"	Journal	14	26 (12)	1023 (9)	39.35	11 (9)	53 (14)	15 (24)	875 (10)	1	1	7	12	17
Information Processing & Management	Journal	14	33 (11)	526 (12)	15.94	3 (36)	20 (23)	30 (10)	506 (11)	0	0	2	8	19
IEEE Transactions on Knowledge and Data Engineering	Journal	13	20 (24)	643 (10)	32.15	6 (16)	55 (12)	14 (28)	588 (10)	0	0	7	11	13
IEEE Transactions on Affective Computing	Journal	12	23 (18)	299 (18)	13	7 (13)	18 (24)	16 (23)	281 (17)	0	0	1	3	13
Journal of the American Society for Information Science and Technology	Journal	10	13 (37)	1314 (4)	101.08	13 (7)	173 (4)	0	1141 (5)	2	3	7	8	10
IEEE International Conference on Data Mining	Proceedings	10	68 (6)	334 (14)	4.91	20 (5)	11 (32)	48 (8)	323 (14)	0	0	1	3	10
Cognitive Computation	Journal	10	28 (14)	240 (23)	8.57	2 (57)	2 (77)	26 (12)	238 (20)	0	0	0	3	11
Information Sciences	Journal	9	19 (25)	388 (13)	20.42	2 (57)	21 (21)	17 (21)	367 (13)	0	1	2	3	8
Neurocomputing	Journal	9	28 (14)	321 (15)	11.46	2 (57)	2 (77)	26 (12)	319 (15)	0	0	1	3	9
Computer Speech and Language	Journal	9	13 (37)	256 (20)	19.69	2 (57)	3 (65)	11 (42)	253 (19)	0	0	2	3	9
Journal of Information Science	Journal	9	22 (19)	201 (24)	9.14	3 (36)	4 (55)	19 (19)	197 (23)	0	0	0	1	9
Computers in Human Behavior	Journal	8	15 (30)	306 (16)	20.4	0	0	15 (24)	306 (16)	0	1	1	3	8
IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining	Proceedings	8	36 (10)	154 (34)	4.28	16 (6)	15 (26)	20 (16)	139 (34)	0	0	0	1	4
Computational Intelligence	Journal; Proceedings	7	9 (72)	579 (11)	64.33	7 (13)	133 (8)	2 (289)	446 (12)	1	2	3	6	6
International Joint Conference on Artificial Intelligence	Proceedings	7	12 (41)	200 (26)	16.67	2 (57)	21 (21)	10 (53)	179 (28)	0	1	1	1	4
Procedia Computer Science	Proceedings	7	63 (7)	272 (19)	4.32	4 (28)	0 (99)	59 (5)	272 (18)	0	0	1	2	6

Abbreviations are the same as Table 8

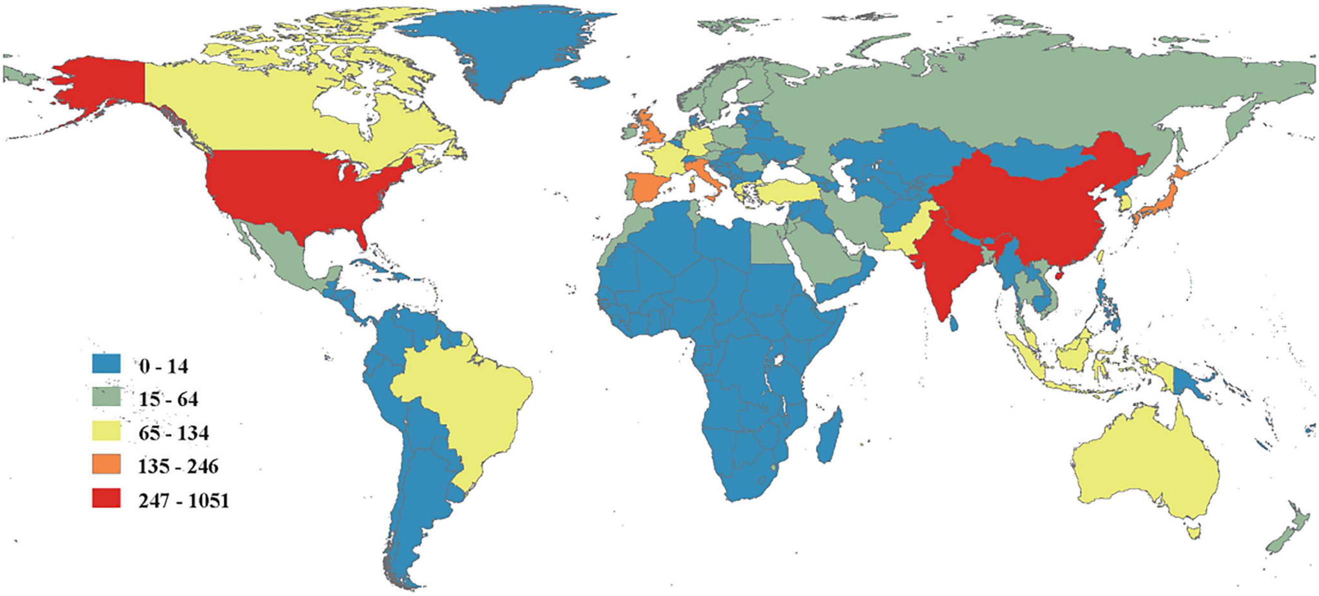

Fig. 6 Geographical distribution of publication counts

Harbin Institute of Technology, and *Beijing University of Posts and Telecommunications*, among which four were from China. In addition, *Erik Cambria* from *Nanyang Technological University* was the most prolific as well as the most influential in the sentiment analysis research. Most of the prolific authors were affiliated with Chinese institutions; however, fewer of them were among the top influential ones. Correspondingly, although institutions and authors from

Table 10 Countries/regions ranked by article count

Country/region	AC	H (R)	CC (R)	ACP	2002–2013		2014–2018		≥200	≥100	≥50	≥25	≥10
					AC (R)	CC (R)	AC (R)	CC (R)					
China	1051	33	5944 (2)	5.66	225 (1)	406 (2)	826 (1)	5538 (2)	2	6	22	49	139
India	559	16	1412 (9)	2.53	63 (3)	45 (13)	496 (2)	1367 (9)	0	1	4	10	32
The USA	552	41	8232 (1)	14.91	110 (2)	1154 (1)	442 (3)	7078 (1)	3	13	34	66	145
The UK	246	30	3814 (3)	15.50	42 (6)	313 (4)	204 (4)	3501 (3)	3	6	20	37	70
Italy	181	21	1549 (7)	8.56	29 (11)	115 (7)	152 (5)	1434 (7)	0	1	7	19	50
Japan	167	14	881 (11)	5.28	49 (4)	104 (8)	118 (7)	777 (11)	0	0	5	12	18
Spain	166	21	1538 (8)	9.27	43 (5)	54 (12)	123 (6)	1484 (8)	0	1	5	19	47
Canada	134	19	3134 (4)	23.39	30 (10)	325 (3)	104 (8)	2809 (4)	3	7	9	15	37
Germany	132	18	2458 (5)	18.62	35 (7)	163 (6)	97 (10)	2295 (5)	3	5	9	12	26
Singapore	128	22	2214 (6)	17.30	26 (12)	282 (5)	102 (9)	1932 (6)	2	5	11	22	41
South Korea	121	13	546 (15)	4.51	33 (8)	42 (15)	88 (11)	504 (15)	0	0	1	4	15
Taiwan	114	14	628 (13)	5.51	26 (12)	69 (11)	88 (11)	559 (13)	0	0	2	9	17
Australia	103	13	543 (16)	5.27	20 (14)	20 (17)	83 (15)	523 (16)	0	0	1	3	22
Hong Kong	101	18	1206 (10)	11.94	32 (9)	104 (8)	69 (19)	1102 (10)	0	1	6	9	33
Malaysia	97	8	252 (24)	2.60	13 (18)	5 (29)	84 (14)	247 (24)	0	0	0	2	7
France	90	11	495 (18)	5.50	20 (14)	20 (17)	70 (18)	475 (18)	0	1	1	5	12
Indonesia	89	5	72 (47)	0.81	2 (42)	0 (39)	87 (13)	72 (47)	0	0	0	0	1
Brazil	83	10	408 (20)	4.92	6 (26)	4 (31)	77 (16)	404 (20)	0	1	1	2	11
Turkey	76	9	229 (27)	3.01	9 (19)	0 (39)	67 (20)	229 (27)	0	0	0	1	9
Pakistan	75	8	292 (22)	3.89	4 (30)	4 (31)	71 (17)	288 (22)	0	0	1	1	7

Abbreviations are the same as Table 8

Table 11 Countries/regions ranked by H-index

Country/region	H	AC (R)	CC (R)	ACP	2002–2013		2014–2018		≥200	≥100	≥50	≥25	≥10
					AC (R)	CC (R)	AC (R)	CC (R)					
The USA	41	552 (3)	8232 (1)	14.91304	110 (2)	1154 (1)	442 (3)	7078 (1)	3	13	34	66	145
China	33	1051 (1)	5944 (2)	5.655566	225 (1)	406 (2)	826 (1)	5538 (2)	2	6	22	49	139
The UK	30	246 (4)	3814 (3)	15.50407	42 (6)	313 (4)	204 (4)	3501 (3)	3	6	20	37	70
Singapore	22	128 (10)	2214 (6)	17.29688	26 (12)	282 (5)	102 (9)	1932 (6)	2	5	11	22	41
Italy	21	181 (5)	1549 (7)	8.558011	29 (11)	115 (7)	152 (5)	1434 (7)	0	1	7	19	50
Spain	21	166 (7)	1538 (8)	9.26506	43 (5)	54 (12)	123 (6)	1484 (8)	0	1	5	19	47
Canada	19	134 (8)	3134 (4)	23.38806	30 (10)	325 (3)	104 (8)	2809 (4)	3	7	9	15	37
Germany	18	132 (9)	2458 (5)	18.62121	35 (7)	163 (6)	97 (10)	2295 (5)	3	5	9	12	26
Hong Kong	18	101 (14)	1206 (10)	11.94059	32 (9)	104 (8)	69 (19)	1102 (10)	0	1	6	9	33
The Netherlands	17	62 (23)	791 (12)	12.75806	14 (17)	14 (23)	48 (23)	777 (11)	0	0	4	8	27
India	16	559 (2)	1412 (9)	2.525939	63 (3)	45 (13)	496 (2)	1367 (9)	0	1	4	10	32
Japan	14	167 (6)	881 (11)	5.275449	49 (4)	104 (8)	118 (7)	777 (11)	0	0	5	12	18
Taiwan	14	114 (12)	628 (13)	5.508772	26 (12)	69 (11)	88 (11)	559 (13)	0	0	2	9	17
South Korea	13	121 (11)	546 (15)	4.512397	33 (8)	42 (15)	88 (11)	504 (15)	0	0	1	4	15
Australia	13	103 (13)	543 (16)	5.271845	20 (14)	20 (17)	83 (15)	523 (16)	0	0	1	3	22
France	11	90 (16)	495 (18)	5.5	20 (14)	20 (17)	70 (18)	475 (18)	0	1	1	5	12
Greece	11	69 (21)	537 (17)	7.782609	18 (16)	83 (10)	51 (22)	454 (17)	0	2	2	3	13
Mexico	11	47 (24)	557 (14)	11.85106	6 (26)	3 (33)	41 (25)	554 (14)	0	1	4	9	11
Switzerland	11	47 (24)	479 (19)	10.19149	9 (19)	6 (28)	38 (26)	473 (19)	0	0	3	5	12

Abbreviations are the same as Table 8

China were productive in publishing sentiment analysis studies, their works' impacts were not as significant as their productivity. Therefore, Chinese institutions and authors are suggested to pay more attention to improve their research impact.

Answers to RQ6 were obtained via scientific collaboration analysis, which demonstrated the close collaboration between countries/regions from the same continents, particularly those from Asia and Europe. Meanwhile, the institutions and authors from the same countries/regions showed closer collaboration in sentiment analysis research. Such features of scientific collaboration were also common in other research fields, as indicated by Song et al. [71]. Furthermore, referring to the topical distribution of prolific authors, authors from the same institutions tended to show similar topic distribution patterns and were also more likely to collaborate (e.g., *Bing Qin* and *Ting Liu*). Also, *Erik Cambria* and *Soujanya Poria*, who had shown similar research interests, used to be colleagues at *Nanyang Technological University*, and both have been researchers at the University of Stirling with Amir Hussain.

Interpretation for Highly Discussed Topics

The STM results provided answers to RQ2. Here, we provide interpretations of the three highly discussed topics. Firstly, *sentiment lexicons and knowledge bases* served as the most highly discussed topic within the studied articles, with a proportion of 9.38%. This indicated that this topic was a prominent issue in the research field. Discriminating terms such as "phrase" and "sentence" within the topic indicated the analysis units. Terms "syntactic" and "semantic" demonstrated their popularity in studies within the topic. There were relevant studies on the topic available. For example, with the purpose of solving the problems of structured-syntactic and lexical-semantic information losses, Zhao et al. [102] integrated syntactic and semantic information into kernels to automatically extract target-polarity collocations. He et al. [103] proposed a lightweight approach to match pattern acquisition to further attain syntactic parsing on several particular Chinese texts consisting of short clauses.

The second most frequently discussed topic was *aspect-based sentiment analysis* (9.09%). Discriminating terms such as "aspect-based," "aspect," "aspect-opinion," and "aspect-level" indicated a significant interest in aspect-based sentiment analysis, while "review" indicated the information material for opinion mining. Aspect-based sentiment analysis is an essential task in opinion mining, aiming to extract explicit aspects of an entity and the sentiments expressed toward each aspect [104]. Recognizing user attitudes toward the various aspects of products, services, and even policies can help improve

Table 12 Institutions ranked by article count

Institution	C/R	AC	H (R)	CC (R)	ACP	2002–2013		2014–2018		≥200	≥100	≥50	≥25	≥10
						AC (R)	CC (R)	AC (R)	CC (R)					
Tsinghua University	China	90	15 (2)	1043 (5)	11.59	27 (2)	49 (22)	63 (2)	994 (5)	1	1	3	9	24
Chinese Academy of Sciences	China	83	14 (3)	1017 (6)	12.25	30 (1)	138 (6)	53 (3)	879 (6)	0	2	5	9	19
Nanyang Technological University	Singapore	82	17 (1)	1370 (3)	16.71	13 (5)	188 (4)	69 (1)	1182 (3)	1	3	7	15	28
Harbin Institute of Technology	China	61	12 (5)	593 (15)	9.72	18 (3)	43 (27)	43 (4)	550 (15)	0	1	2	6	14
Beijing University of Posts and Telecommunications	China	56	5 (50)	137 (81)	2.45	17 (4)	8 (88)	39 (6)	129 (81)	0	0	0	2	2
Indian Institute of Technology	India	48	8 (15)	225 (35)	4.69	10 (13)	15 (52)	38 (7)	210 (35)	0	0	1	3	8
National Institute of Technology	India	46	7 (19)	180 (50)	3.91	3 (62)	2 (176)	43 (4)	178 (50)	0	0	1	1	5
Beihang University	China	39	5 (50)	88 (132)	2.26	5 (31)	0 (296)	34 (8)	88 (132)	0	0	0	0	3
University of Tokushima	Japan	36	6 (34)	142 (77)	3.94	13 (5)	12 (68)	23 (11)	130 (77)	0	0	0	2	3
Hefei University of Technology	China	34	7 (19)	230 (33)	6.76	5 (31)	3 (140)	29 (9)	227 (33)	0	0	1	3	5
City University of Hong Kong	Hong Kong	31	11 (7)	397 (22)	12.81	6 (21)	13 (65)	25 (10)	384 (22)	0	0	2	5	11
University of Technology, Malaysia	Malaysia	31	4 (76)	90 (128)	2.90	8 (17)	5 (118)	23 (11)	85 (128)	0	0	0	1	1
Hong Kong Polytechnic University	Hong Kong	30	11 (7)	554 (17)	18.47	13 (5)	79 (12)	17 (24)	475 (17)	0	1	4	4	11
Peking University	China	30	6 (34)	99 (114)	3.30	11 (9)	12 (68)	19 (20)	87 (114)	0	0	0	0	3
Shanghai Jiao Tong University	China	25	6 (34)	243 (31)	9.72	11 (9)	11 (71)	14 (37)	232 (31)	0	0	3	3	5
Erasmus University Rotterdam	The Netherlands	24	9 (11)	267 (28)	11.13	9 (15)	10 (78)	15 (32)	257 (28)	0	0	2	2	8
National University of Defense Technology	China	24	3 (144)	53 (221)	2.21	1 (207)	1 (222)	23 (11)	52 (223)	0	0	0	0	1
Jordan University of Science and Technology	Jordan	23	9 (11)	194 (44)	8.43	3 (62)	0 (296)	20 (16)	194 (44)	0	0	0	2	7

Abbreviations are the same as Table 8, except *C/R*, country/region

Table 13 Institutions ranked by H-index

Institution	C/R	H	AC (R)	CC (R)	ACP	2002–2013		2014–2018		≥200	≥100	≥50	≥25	≥10
						AC (R)	CC (R)	AC (R)	CC (R)					
Nanyang Technological University	Singapore	17	82 (3)	1370 (3)	16.71	13 (5)	188 (4)	69 (1)	1182 (3)	1	3	7	15	28
Tsinghua University	China	15	90 (1)	1043 (5)	11.59	27 (2)	49 (22)	63 (2)	994 (5)	1	1	3	9	24
Chinese Academy of Sciences	China	14	83 (2)	1017 (6)	12.25	30 (1)	138 (6)	53 (3)	879 (6)	0	2	5	9	19
University of Stirling	The UK	13	22 (19)	573 (16)	26.05	5 (31)	30 (35)	17 (24)	543 (16)	0	0	5	10	14
Harbin Institute of Technology	China	12	61 (4)	593 (15)	9.72	18 (3)	43 (27)	43 (4)	550 (15)	0	1	2	6	14
University of Wolverhampton	The UK	12	19 (34)	1408 (2)	74.11	11 (9)	180 (5)	8 (96)	1228 (2)	3	4	5	7	12
City University of Hong Kong	Hong Kong	11	31 (11)	397 (22)	12.81	6 (21)	13 (65)	25 (10)	384 (22)	0	0	2	5	11
Hong Kong Polytechnic University	Hong Kong	11	30 (13)	554 (17)	18.47	13 (5)	79 (12)	17 (24)	475 (17)	0	1	4	4	11
The University of Arizona	The USA	11	21 (23)	631 (11)	30.05	13 (5)	126 (8)	8 (96)	505 (12)	0	1	6	7	12
University of Illinois at Chicago	The USA	10	18 (39)	496 (19)	27.56	5 (31)	54 (18)	13 (46)	442 (19)	1	2	2	3	10
Erasmus University Rotterdam	The Netherlands	9	24 (16)	267 (28)	11.13	9 (15)	10 (78)	15 (32)	257 (28)	0	0	2	2	8
Jordan University of Science and Technology	Jordan	9	23 (18)	194 (44)	8.43	3 (62)	0 (296)	20 (16)	194 (44)	0	0	0	2	7
National Polytechnic Institute	Mexico	9	19 (34)	445 (21)	23.42	1 (207)	2 (176)	18 (22)	443 (21)	0	1	4	7	9
University of Amsterdam	The Netherlands	9	13 (65)	293 (25)	22.54	2 (109)	3 (140)	11 (60)	290 (25)	0	0	1	5	9
Indian Institute of Technology	India	8	48 (6)	225 (35)	4.69	10 (13)	15 (52)	38 (7)	210 (35)	0	0	1	3	8
University of Jaen	Spain	8	15 (47)	287 (27)	19.13	6 (21)	16 (48)	9 (79)	271 (27)	0	0	3	3	6
Massachusetts Institute of Technology	The USA	8	9 (117)	631 (11)	70.11	5 (31)	33 (32)	4 (297)	598 (11)	1	1	3	6	6
National Research Council	Canada	8	8 (144)	1261 (4)	157.63	3 (62)	127 (7)	5 (224)	1134 (4)	1	3	3	6	8

Abbreviations are the same as Table 12

Table 14 Authors ranked by article count

Author	Current institution	AC	CC (R)	ACP	H (R)	2002–2013		2014–2018		≥200	≥100	≥50	≥25	≥10
						AC (R)	CC (R)	AC (R)	CC (R)					
Erik Cambria	*Nanyang Technological University*	45	836 (8)	18.58	16 (1)	0	6 (231)	45 (1)	815	0	2	6	12	19
Fuji Ren	*Tokushima University*	38	165 (79)	4.34	7 (10)	14 (1)	12 (144)	24 (2)	153	0	0	0	2	4
Amir Hussain[*]	*Edinburgh Napier University*	22	573 (14)	26.05	13 (2)	5 (17)	30 (65)	17 (4)	542	0	0	5	10	14
Flavius Frasincar	*Erasmus University Rotterdam*	19	186 (59)	9.79	8 (8)	6 (14)	8 (190)	13 (5)	178	0	0	1	1	6
Soujanya Poria	*Singapore University of Technology and Design*	18	480 (18)	26.67	11 (3)	0	0 (837)	18 (3)	467	0	2	4	6	11
Yongfeng Huang	*Tsinghua University*	15	62 (342)	4.13	5 (26)	2 (128)	0 (837)	13 (5)	62	0	0	0	0	3
Alexander Gelbthe UKh	*National Polytechnic Institute*	14	438 (22)	31.29	9 (5)	1 (356)	2 (450)	13 (5)	422	0	1	4	7	9
Mike Thelwall	*University of Wolverhampton*	14	1357 (4)	96.93	10 (4)	10 (2)	168 (5)	4 (146)	1189	3	4	5	7	10
Ting Liu	*Harbin Institute of Technology*	14	107 (148)	7.64	7 (10)	2 (128)	0 (837)	12 (9)	107	0	0	0	2	5
Bing Qin	*Harbin Institute of Technology*	13	82 (212)	6.31	6 (18)	2 (128)	0 (837)	11 (12)	82	0	0	0	1	4
Hua Xu	*Tsinghua University*	13	156 (83)	12.00	6 (18)	6 (14)	14 (123)	7 (34)	141	0	0	0	3	5
Kam-Fai Wong	*Chinese University of Hong Kong*	13	90 (184)	6.92	4 (45)	8 (6)	11 (146)	5 (85)	79	0	0	0	1	3
Mahmoud Al-Ayyoub	*Jordan University of Science and Technology*	13	82 (212)	6.31	5 (26)	2 (128)	0 (837)	11 (12)	82	0	0	0	1	3
Xiao Sun	*Hefei University of Technology*	13	19 (1192)	1.46	2 (246)	0	0 (837)	13 (5)	19	0	0	0	0	0

Abbreviations are the same as Table 8

[*] Amir Hussain is currently with Edinburgh Napier University, UK; his previous affiliation was with the University of Stirling, UK

Table 15 Authors ranked by H-index

Author	Current institution	H	AC (R)	CC (R)	ACP	2002–2013		2014–2018		≥200	≥100	≥50	≥25	≥10
						AC (R)	CC (R)	AC (R)	CC (R)					
Erik Cambria	*Nanyang Technological University*	16	45 (1)	836 (8)	18.58	0	6 (231)	45 (1)	815	0	2	6	12	19
Amir Hussain[*]	*Edinburgh Napier University*	13	22 (3)	573 (14)	26.05	5 (17)	30 (65)	17 (4)	542	0	0	5	10	14
Soujanya Poria	*Singapore University of Technology and Design*	11	18 (5)	480 (18)	26.67	0	0 (837)	18 (3)	467	0	2	4	6	11
Mike Thelwall	*University of Wolverhampton*	10	14 (7)	1357 (4)	96.93	10 (2)	168 (5)	4 (146)	1189	3	4	5	7	10
Alexander Gelbthe UKh	*National Polytechnic Institute*	9	14 (7)	438 (22)	31.29	1 (356)	2 (450)	13 (5)	422	0	1	4	7	9
Hsinchun Chen	*The University of Arizona*	9	12 (15)	452 (20)	37.67	9 (3)	102 (15)	3 (256)	339	0	1	5	5	8
Bing Liu	*University of Illinois at Chicago*	9	11 (22)	442 (21)	40.18	5 (17)	54 (29)	6 (48)	387	1	2	2	3	7
Flavius Frasincar	*Erasmus University Rotterdam*	8	19 (4)	186 (59)	9.79	6 (14)	8 (190)	13 (5)	178	0	0	1	1	6
Georgios Paltoglou	*European Commission*	8	9 (39)	994 (5)	110.44	8 (6)	106 (14)	1 (1625)	888	2	2	3	4	8
Fuji Ren	*Tokushima University*	7	38 (2)	165 (79)	4.34	14 (1)	12 (144)	24 (2)	153	0	0	0	2	4
Ting Liu	*Harbin Institute of Technology*	7	14 (7)	107 (148)	7.64	2 (128)	0 (837)	12 (9)	107	0	0	0	2	5
Daniel Zeng	*University of Arizona and Chinese Academy of Sciences*	7	12 (15)	193 (52)	16.08	7 (9)	31 (64)	5 (85)	162	0	0	1	2	5
Alexander Hogenboom	*Erasmus University Rotterdam*	7	10 (28)	111 (141)	11.10	7 (9)	10 (159)	3 (256)	101	0	0	0	0	4
L. Alfonso Urena-Lopez	*University of Jaen*	7	9 (39)	202 (46)	22.44	3 (57)	9 (178)	6 (48)	193	0	0	2	2	4
Eugenio Martinez-Camara	*University of Granada*	7	8 (46)	115 (129)	14.38	2 (128)	3 (363)	6 (48)	112	0	0	1	1	3
M. Teresa Martin-Valdivia	*University of Jaen*	7	8 (46)	202 (46)	25.25	3 (57)	9 (178)	5 (85)	193	0	0	2	2	4
Saif M. Mohammad	*National Research Council Canada*	7	7 (64)	486 (16)	69.43	2 (128)	1 (582)	5 (85)	485	0	2	2	5	7

Abbreviations are the same as Table 8

[*] Amir Hussain is currently with Edinburgh Napier University, UK; his previous affiliation was with the University of Stirling, UK

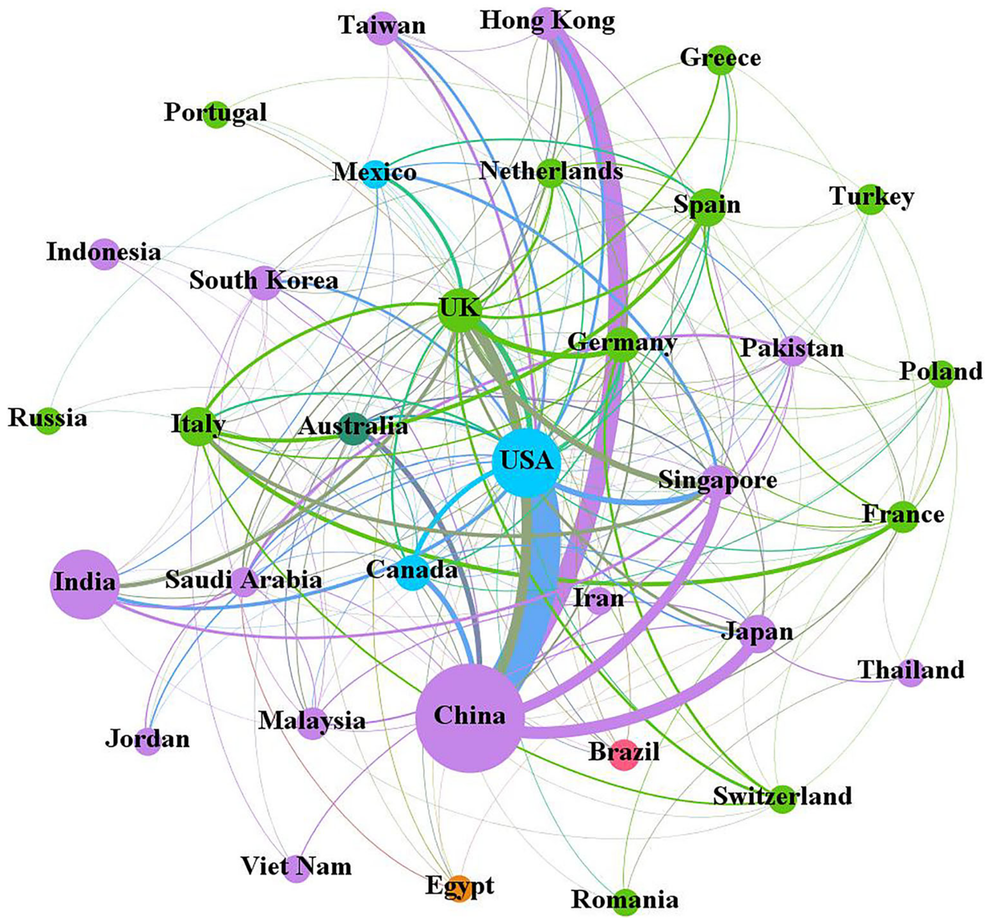

Fig. 7 Collaboration network of countries/regions with an article count ≥ 30

innovation. Therefore, aspect-based sentiment analysis has also become a growingly popular task in NLP [105]. Relevant studies were primarily concerned with the exploration of the sentiment polarity in accordance with the explicit aspects of various products and services [106]. For example, Qasem et al. [107] introduced a novel constrained ant clustering method and applied it to the identification of the aspect category in product reviews. Omurca et al. [108] proposed a graph-driven Laplace smoothing approach to extract implicit aspects hidden in hotel reviews in Turkish. The term "product" indicated the object toward which the subject expressed their reviews or opinions. The terms "merchant" and "e-commerce" indicated that most relevant studies were about buyers' reviews on products or services purchased through online channels. Product reviews provided by online buyers are valuable data sources for potential new buyers who are considering making purchase decisions. It has become increasingly essential to analyze the customer reviews and to further extract the opinions or reviews toward the products bought by customers, especially with the large volumes of data being posted on e-commerce sites continuously [109]. Thus, opinion mining is becoming more significant than it has ever been, especially for the analysis and prediction of customer behavior for commercial purposes. Studies that aimed to achieve effective opinion mining are currently available. For example, by proposing a novel multifacet sentiment analysis method to examine consumer review dimensions, Liang et al. [110] explored the effects of the sentiments of different topics within online reviews on the sale of an app. Singh et al. [109] presented a novel approach based on machine learning to predict the helpfulness of customer reviews by applying different textual features, such as polarity, subjectivity, entropy, and reading ease.

The third most frequent topic was *social network analysis* (8.79%) with discriminating terms such as "retweet," "tweet," "twitter," "hashtag," "facebook," "social media," and "networking." With the constantly growing usage of the Internet, social media has become a platform for opinion sharing [111]. Sentiment analysis has emerged to be an essential task in the applications with e-commerce, politics, and social sciences [112]. As one of the most well-known social networking sites, Twitter allows users to share small textual information at any time or location [113]. It also provides an opportunity for

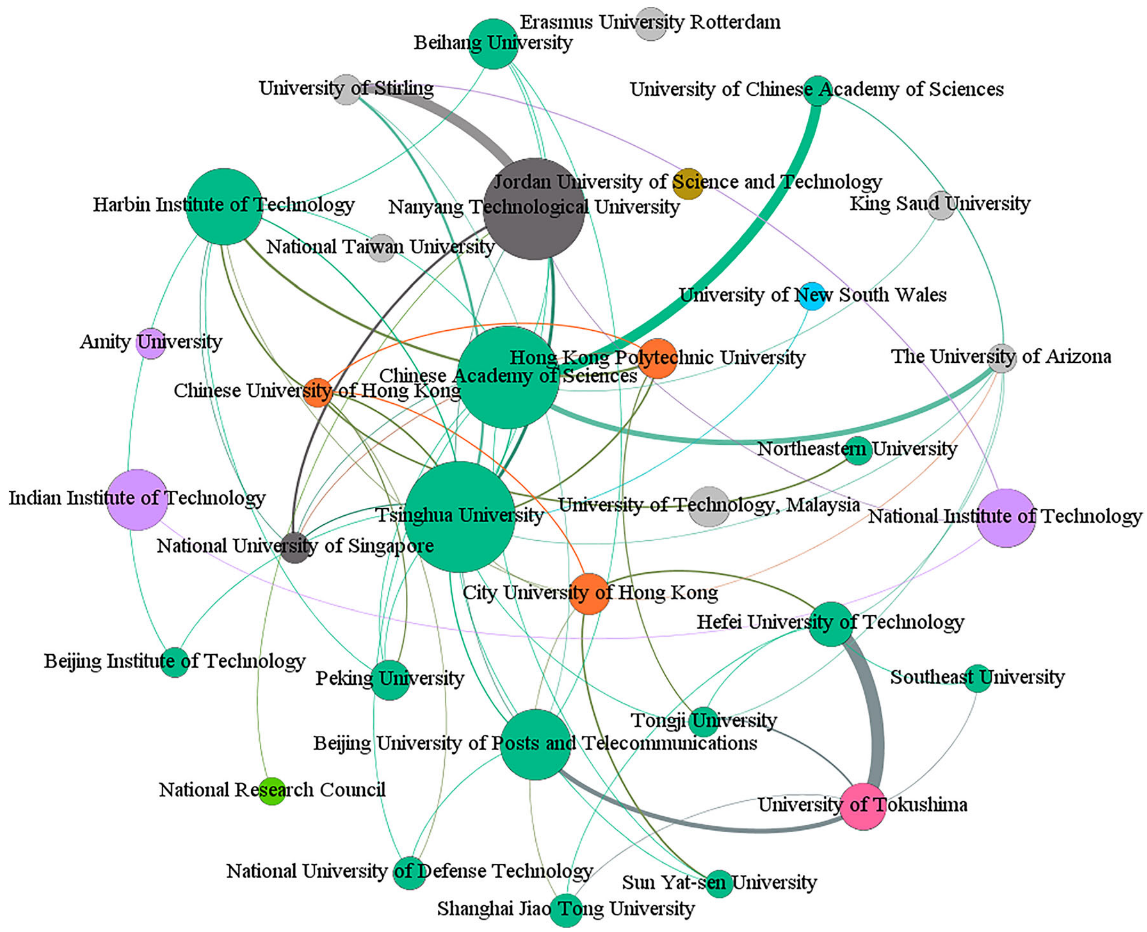

Fig. 8 Collaboration network of affiliations with an article count ≥ 20

scholars to explore users' attitudes toward social or political issues, such as natural calamities and elections [114]. Therefore, terms such as "leader," "event," "football," "bitcoin," "soccer," and "fan" appeared. For example, Singh et al. [115] attempted to construct a relationship between the large volume of tweets data produced during the campaigning period and the final voting share received by different political parties in the Spanish general elections. Dinkić et al. [116] mined and analyzed data from Twitter in terms of content classification, language determination, and sentiment analysis.

Future Potential Research Directions

By combining the results of the topical temporal trends, MK test results, and topical proportion, some implications for future research directions (RQ3) could be obtained. We recognized five topics with increasing interest from the results of topical temporal trends and the MK test, which could be categorized into application-oriented and methodology-oriented topics concerning sentiment analysis. The methodology-oriented topic involved *deep learning for natural language processing*, while the application-oriented topics included *social network analysis*, *web services*, *recommender systems and personalization*, and *education and social issues*.

Deep learning for natural language processing had experienced an increase in interest, particularly since about 2015. As indicated by Purnamasari et al. [117], an essential challenge in sentiment analysis is the incorporation of NLP to make machines better understand human languages. In the past decade, the applications of deep-learning techniques have prompted the development of NLP research [118]. In addition, advances in deep learning and neural network models have a significant impact on sentiment analysis, which could be validated by the fact that the models based on RNNs or CNNs can outperform non-neural models such as SVM [119]. CNNs and RNNs serve as two major deep-learning techniques in text and sentence modeling [118]. For example, Huang et al. [120] aimed to detect the sentiment strength by using context-dependent lexicon-based CNNs. Sato et al. [121] highlighted the effectiveness of ConvNets in extracting meaningful representations from both English and Japanese corpus.

From the application perspective, four topics had received increasing attention from scholars. First, studies regarding

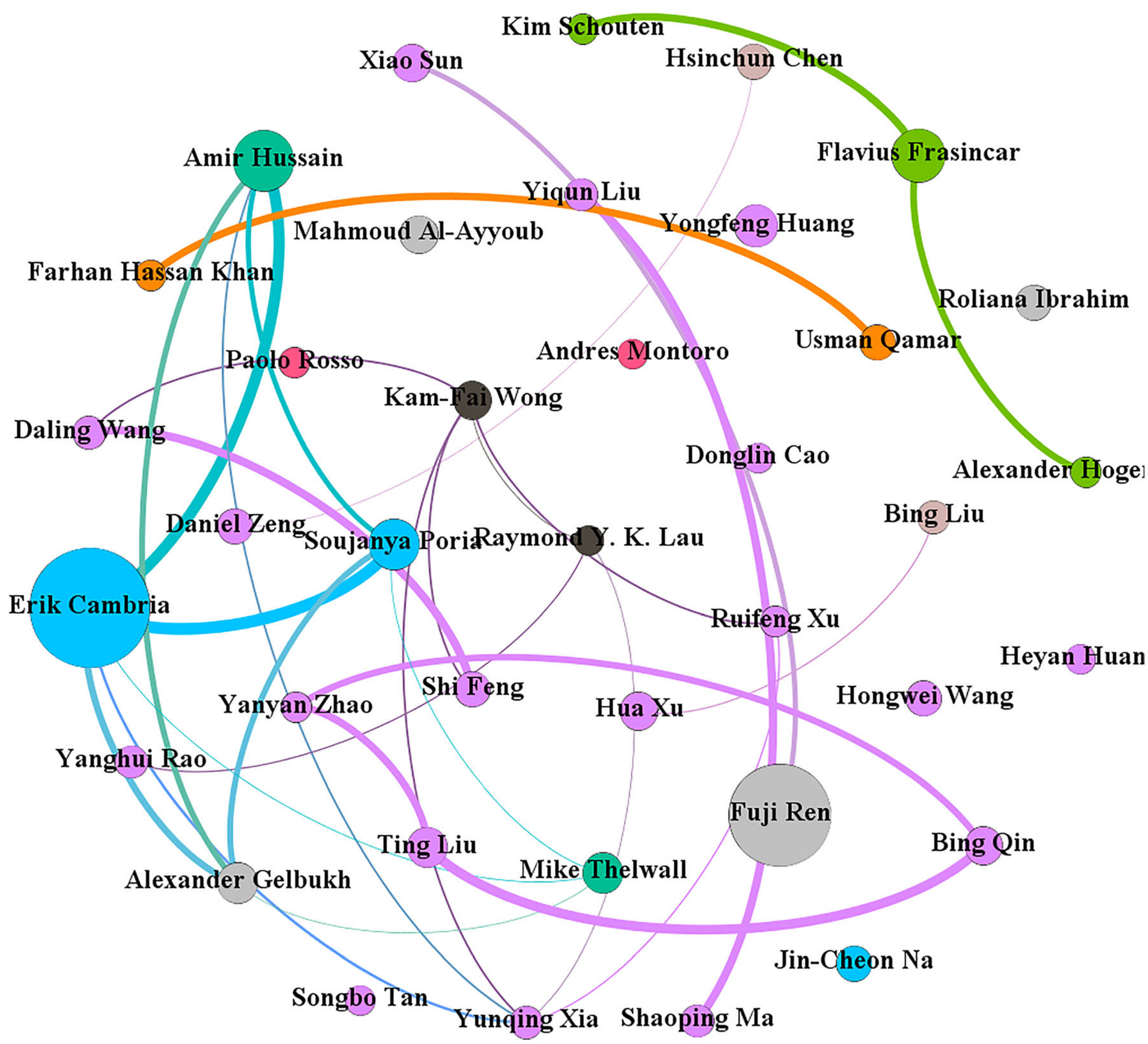

Fig. 9 Collaboration network of authors with an article count ≥ ten

users' sentiments using social networks such as Twitter continuously increased [122], particularly in the last few years. More discussions on the topic are available in the "Interpretation for Highly Discussed Topics" section. As the Internet becomes a necessity in people's lives, there is a dramatic growth in a variety of online service companies. Furthermore, to maintain an active status and stay competitive in the market, companies must assess client satisfaction with their products or services. The tremendous prevalence and popularity of web-based social media have attracted the attention of companies to take advantage of the substantial sentiment data that is valuable for business intelligence.

Second, issues concerning *recommender systems and personalization* had received significantly increasing attention, reaching a peak around the year 2010. For example, to enhance recommendation, Chen et al. [123] first developed a tensor matrix factorization method for learning to rank user preferences based on phrase-level sentiment analysis across different categories. They then incorporated the developed technologies into collaborative filtering to propose a novel model. Experiments on two real-world datasets indicated the prominent performance of the proposed method in capturing users' features of interest and recommending suitable items in comparison to the state-of-the-art methods. Chen et al. [124] depicted how the analysis of big social data could help airline companies understand their customers better to further enhance customer relationship management by applying sentiment analysis. Yun et al. [125] proposed a novel hybrid collaborative filtering recommendation system through the sentiment analysis of purchase reviews.

Third, sentiment analysis had also been widely applied in web services, such as airlines, tourist portals, disasters, and sales. For example, Yan et al. [126] aimed to examine the relationship between emotion tendency and electronic word-of-mouth publishing at different stages of tourists' travel experiences. Results showed that positive emotions were more common during journeys. In addition, the emotions of men and women differed. Jayaratna et al. [127]

explored the adaptation of subjective metrics in social media to examine cloud service performance. They first identified subjective factors driving cloud consumers to or from buying cloud services, and then explored the relationship between the consumers' attitudes and the identified factors related to the growth of cloud market revenue. Their findings indicated that subjective metrics could be a predictor for cloud services marketing.

Finally, issues concerning *education and social issues* had also shown popularity and prevalence in sentiment analysis studies. Opinions are essential for decision-making in education domains to help teachers improve their pedagogical strategies and to enable learners to make decisions about education resources [128]. Teacher evaluation is an important issue in educational institutions, and students' opinion is one of the main sources used for sentiment analysis [129]. Chauhan et al. [130] explored the potential adoption of aspect-based sentiment analysis of learners' feedback to improve teaching and learning processes. Santos et al. [131] presented a novel institutional teaching evaluation method by utilizing sentiment analysis to identify positive or negative teaching practices from students' perspectives in a higher education institution.

Topical Proportion Distributions for Prolific Actors

The visualization of topical distributions for prolific actors provided answers to RQ4. Some implications could be drawn from the analyses. Compared to institutions and authors, countries/regions tended to show a relative balance in interest for each topic. Moreover, the topical distribution patterns for most countries were quite similar, particularly the USA and the UK, indicating that for these countries, studies on sentiment analysis were flourishing with the consideration of every specific issue. In addition, almost all countries/regions showed particular interests on topics such as *aspect-based sentiment analysis*, *sentiment lexicons and knowledge bases*, and *social network analysis*, all of which were the most frequently discussed topics. For other topics, there were particular countries/regions showing great interest in them. For example, India, Taiwan, and Singapore were particularly active in *deep learning for natural language processing*. For *bio-signals and emotion model*s, countries/regions such as Spain, Canada, and Germany showed great interest.

Furthermore, authors tended to show similar topical distribution patterns with their affiliated institutions. For example, *Fuji Ren* was affiliated with the *University of Tokushima*, and his topical distribution pattern was similar to the *University of Tokushima*. To be specific, he was mainly active in *aspect-based sentiment analysis* and *topic model*, which were also research foci for the *University of Tokushima*.

As indicated by the network-based investigation on scientific collaborations, countries/regions, institutions, or authors with similar research interests were more inclined to conduct collaborative research; for example, *Ting Liu* and *Bing Qin*, who were both affiliated with *Harbin Institute of Technology*. However, it is also suggested that those with different research interests can conduct collaborations. This could result in a new research direction wherein different kinds of knowledge, skill, and expertise are combined.

Special Issues Concerning Sentiment Analysis

Here, we also provide analyses and discussions on the trends and topics of special issues concerning sentiment analysis. In addition to the 15 special issues listed in the SenticNet[6] website, we also conducted a search in nine commonly used databases on 20th February 2020. A total of 108 special issues were identified to be relevant. The detailed process of data retrieval and screening is depicted in Table S2 in the Appendix. Figure 10 shows the trend of special issues related to sentiment analysis, from which it could be observed that during the period 2008–2019, the number of special issues related to sentiment analysis had experienced a significant increase, demonstrating a wide and growing concern toward sentiment analysis. Examples of representative special issues related to sentiment analysis are listed in Table S3 in the Appendix.

For the 108 special issues, we collected the full text of their editorials and further extracted their key phrases by using a self-developed program based on Natural Language Toolkit.[7] Table 16 lists some of the important key phrases, from which several implications about the trends of topics concerned by the special issues related to sentiment analysis could be obtained, as elaborated in the following paragraphs.

First, "deep learning" started to appear within the special issues around 2016, and since then, it continued to gain attention, particularly in the last 2 years. Moreover, scholars focused more on relevant techniques such as "deep reinforcement" and "deep reinforcement learning" in the last 2 years.

Second, big data analytics started to attain popularity around 2014 and had received constantly increasing interest, particularly since about 2017. There were several recent special issues with a particular focus on big data analytics. For example, within a special issue on "Cognitive big data analytics for business intelligence applications: toward performance improvement" by Elhoseny et al., there was a paper presented by Maqsood et al. [132], in which they proposed an innovate approach based on deep learning to predict stock prices.

Third, decision support–related issues started to become an interest among authors in 2014, and since then, they continued to be research foci, particularly in the recent 2 years, with the appearance of relevant terms such as "intelligent decision support system," "decision making," "decision support,"

[6] https://sentic.net/
[7] www.nltk.org

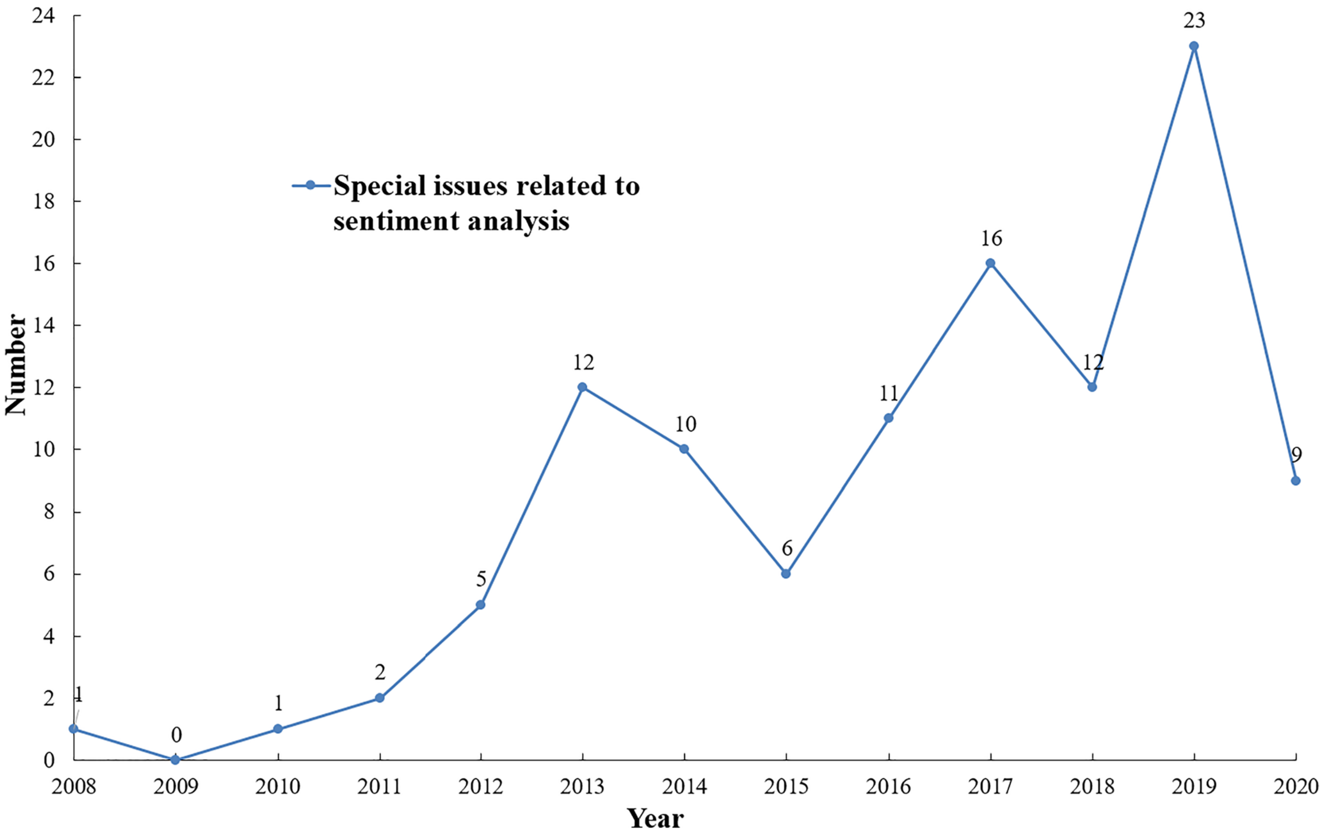

Fig. 10 Trend of special issues related to sentiment analysis

"decision-making process," and "customer decision-making process." For example, within a special issue on "Intelligent decision support systems based on soft computing and their applications in real-world problems" by Herrera-Viedma et al., there was a paper by García-Díaz et al. [133], in which they presented a platform to automatically process information collected from social networks, with a particular focus on the improvement of the accuracy of decision support systems for sentiment analysis.

Fourth, several smart-related terms (e.g., "smart city," "smart grid," "smart home," and "smart tourism") started to appear in 2017 and were examined the most in 2019 within several special issues. As indicated by Koo and Cantoni in a special issue on "Informatics/data analytics in smart tourism," although informatics and data analysis (for example, the use of user-generated contents for tasks such as automatic information extraction, topic identification, as well as opinion and sentiment mining) were of noteworthy potential in smart tourism research, they received scarce attention. However, there had been growing concerns about the application of sentiment analysis to different fields to facilitate the development of new landscapes such as "smart city," "smart home," and "smart tourism," particularly in the past 2 years.

Fifth, several cognitive-related terms such as "cognitive process," "cognitive appraisal theory," "cognitive diagnosis," and "cognitive response" had become topics of interest for scholars, particularly in the last 2 years. Relevant special issues were found to be concerned with big data analytics, for example, a special issue on "Cognitive big data analytics for business intelligence applications: towards performance improvement" by Elhoseny et al.

Sixth, special issues regarding a recently emerged topic, i.e., word representations for sentiment analysis, had been available, with relevant terms such as "word representation" and "neighboring word representation" appearing in the last 2 years. For example, within a special issue on "Enabling technologies for social Internet of Things" by Imran et al., a paper by Ma et al. [134] proposed a feature-driven compositing memory network for improving classification accuracy in large-scale corpus to further enhance aspect-based sentiment classification in social Internet of Things.

Moreover, different soft computing techniques (e.g., DNNs and fuzzy logic) had gained momentum in the past years for addressing NLP and knowledge representation issues. Such techniques are accompanied by a boost in application-specific methodologies that can emulate the cognitive processes behind decision-making. Soft computing techniques have received attention from authors in the sentiment analysis community since 2017, as witnessed from topics of special issues, for example, an ongoing special issue on "Soft computing for recommender systems and sentiment analysis" by Malandri et al.

Table 16 Examples of important key phrases concerned by special issues concerning sentiment analysis

Key phrases	2008	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2008–2020	2008–2014	2015–2020	2018–2020
Machine learning				1	1	3	4	6	3	3	10	4	35	5	30	17
Artificial intelligence						3		3	6	6	11	3	32	3	29	20
Neural network			1	1		1		4	5	4	9	4	29	3	26	17
Natural language processing	1				3	5		5	1	1	4	5	25	9	16	10
Big data analytics						2	1		5	1	4	1	14	2	12	6
Deep learning								1	2	1	5	4	13	0	13	10
Computational intelligence						2		1	3	3	2	1	12	2	10	6
Decision making						1	1	1	2	1	3	2	11	1	10	6
Feature selection							1	1	1	4	2	1	10	0	10	7
Fuzzy logic									2	3	4	1	10	0	10	8
Affective computing					1	1		1	1		4	1	9	2	7	5
Decision support							1	1	2	1	2	2	9	0	9	5
Stock market								1	2	3	1	2	9	0	9	6
Decision-making process								1	1		2	4	8	0	8	6
Emotion classification					1	1				1	4	1	8	2	6	6
Graph mining						1		1			1	5	8	1	7	6
Genetic algorithm			1					1	2	2	1		7	1	6	3
Mobile device					1		1	1	2		2		7	1	6	2
Bayesian network								1		2	3		6	0	6	5
Feature extraction			1				1				3	1	6	1	5	4
Human–computer interaction					2						4		6	2	4	4
Mobile application									2		4		6	0	6	4
Particle swarm optimization			1						2	1	2		6	1	5	3
Soft computing						1		1	2	1		1	6	1	5	2
Ad hoc				1					1		3		5	1	4	3
Business intelligence							1	2	1			1	5	0	5	1
Fuzzy c-means									3		1	1	5	0	5	2
Fuzzy set								2	2	1			5	0	5	1
Mobile technology							1				3	1	5	0	5	4
Aspect-based sentiment analysis										1	3		4	0	4	4
Collaborative filtering								1		1	2		4	0	4	3
Reinforcement learning								1			3		4	0	4	3
Smart city									1		2	1	4	0	4	3
Smart grid									1		3		4	0	4	3

Table 16 (continued)

Key phrases	2008	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2008–2020	2008–2014	2015–2020	2018–2020
Smart grid									1		3		4	0	4	3
Mobile interface											1	2	3	0	3	3
Personalized recommendation										1		2	3	0	3	3
Virtual machine											3		3	0	3	3
Smart home											3		3	0	3	3
Smart tourism									1		1	1	3	0	3	2
Aspect extraction								1				1	2	0	2	1
Cognitive process											1	1	2	0	2	2
Deep reinforcement										1	1		2	0	2	2
Intelligent decision support system										1		1	2	0	2	2
Multi-task learning											2		2	0	2	2
Word representation											2		2	0	2	2
Sentic computing												2	2	0	2	2
Information fusion						1						1	2	1	1	1
Aspect-level lstm											1		1	0	1	1
Cognitive appraisal theory												1	1	0	1	1
Cognitive diagnosis												1	1	0	1	1
Cognitive response												1	1	0	1	1
Customer decision-making process												1	1	0	1	1
Deep reinforcement learning											1		1	0	1	1
Emotional recognition edge device											1		1	0	1	1
Feature recognition											2		1	0	1	1
Neighboring word representation											1		1	0	1	1
Image information fusion											1		1	0	1	1
Multi-sensor information fusion model											1		1	0	1	1

Besides, the term “information fusion” had been focused on in the last 2 years, with the appearance of relevant terms, such as “information fusion,” “image information fusion,” and “multi-sensor information fusion model,” within special issues on sentiment analysis. Two very relevant special issues were found. The first one was “Information fusion for affective computing and sentiment analysis” by Hussain et al. The second one was “Research on methods of multimodal information fusion in emotion recognition” by Xia et al. In addition, there is a new special issue “A Decade of Sentic Computing” in Cognitive Computation by Cambria and Hussain. Sentic computing addresses issues in NLP by using a multidisciplinary method to bridge the gap between statistical NLP and other disciplines (e.g., linguistics, commonsense reasoning, and affective computing), which is necessary for understanding human languages.

Latest Trends in Sentiment Analysis Research

The latest trends in sentiment analysis research are presented here to provide insights into the most recent research. The latest trends in deep-learning-based aspect extraction and sentiment analysis should be highlighted (e.g., [135–138]), which have been demonstrated and covered in the identified topic *deep neural networks*. For instance, Dashtipour et al. [39] presented an innovative hybrid-based approach regarding the application of concept-level sentiment analysis to the Persian language, which combined linguistic rules and deep learning to improve polarity detection. Experiments on benchmark Persian product and hotel reviews demonstrated that their approach outperformed the state-of-the-art methods. Ma et al. [2, 139] presented a knowledge-rich solution for targeted aspect-based sentiment analysis, particularly emphasizing on the leverage of commonsense knowledge in the deep neural sequential model. Their method tackled the challenges of both targeted and aspect-based sentiment analyses by exploiting commonsense knowledge. Majumder et al. [140] proposed an innovative method based on RNNs, which traced and adopted information about individual party states during conversations to classify emotions. Experiments on two different datasets demonstrated the effectiveness of their method.

Moreover, some latest studies are focusing on word representations for sentiment analysis as well as on capsule networks for challenging NLP applications. Song et al. [41] proposed an approach of sentiment lexicon embedding that better represented sentiment word's semantic relationships than existing word embedding techniques without manually-annotated sentiment corpus. Zhao et al. [141] described an agreement score for evaluating the performance of routing processes at the instance level and proposed an adaptive optimizer to enhance the reliability of routing. Experimental results demonstrated the effectiveness of their approach in comparison to strong competitors on two NLP tasks, including question answering and multilabel text classification.

In addition, some latest studies on aspect-based sentiment analysis can also be found. For example, Peng et al. [142] introduced the adaptive embeddings learning method for appending sentence context to aspect targets. Experiments demonstrated the effectiveness of their method. Majumder et al. [143] presented an innovative approach called interaspect relation modeling for aspect-based sentiment analysis by integrating the relevant information on the neighboring aspects into sentiment classification of target aspect with the use of memory networks. Experiments on restaurant and laptop domains demonstrated that their method outperformed the state-of-the-art methods. Al-Smadi et al. [144] proposed a novel method for aspect-based sentiment analysis of Arabic reviews of hotels with the use of supervised machine learning. They employed state-of-the-art methods for training a set of classifiers with morphological, syntactic, and semantic features to solve three research tasks, including aspect category identification, opinion target expression extraction, and sentiment polarity identification.

Conclusion

By performing an STM-based bibliometric analysis on the articles in relation to sentiment analysis, this study provided a thorough review of the research field by identifying the major contributors in terms of productivity and impact, visualizing scientific collaborations, and in particular, revealing the prominent topics, along with their development and evolution, as well as the diverse distributions of these topics among various types of research units. The articles and citations associated with sentiment analysis demonstrated significant growth throughout the past years.

Admittedly, the findings were acquired with the use of only one database, i.e., Web of Science. Further explorations with an extension to more databases such as the Scopus are required. Furthermore, it would be interesting to explore the evolution of the research topics by combining statistical analysis techniques such as time series analysis with topic modeling. This would offer a deeper understanding of the research trend of sentiment analysis.

Nevertheless, the findings in this study could yield a better understanding of the latent topical popularity, evolution, distribution across predominant units, as well as the intercountry/region collaborations in sentiment analysis research. These could serve as a guide for scholars and project managers to better allocate resources in future research and project management.

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Compliance with Ethical Standards

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References

1. Tirea M. Traders' behavior effect on stock price evolution. 2013 15th International Symposium on Symbolic and Numeric Algorithms for Scientific Computing: IEEE; 2013. p. 273–280.
2. Ma Y, Peng H, Khan T, Cambria E, Hussain A. Sentic LSTM: a hybrid network for targeted aspect-based sentiment analysis. Cogn Comput. 2018;10(4):639–50.
3. Agt-Rickauer H, Kutsche R-D, Sack H. Automated recommendation of related model elements for domain models. International conference on model-driven engineering and software development: Springer; 2018. p. 134–58.
4. Ravi K, Ravi V. A survey on opinion mining and sentiment analysis: tasks, approaches and applications. Knowl-Based Syst. 2015;89:14–46.
5. Hussein D. A survey on sentiment analysis challenges. J King Saud Univ Eng Sci. 2018;30(4):330–8.
6. Liu B. Sentiment analysis and opinion mining. Synth Lect Hum Lang Technol. 2012;5(1):1–167.
7. Qazi A, Raj RG, Hardaker G, Standing C. A systematic literature review on opinion types and sentiment analysis techniques. Internet Res. 2017;27(3):608–30.
8. Medhat W, Hassan A, Korashy H. Sentiment analysis algorithms and applications: a survey. Ain Shams Eng J. 2014;5(4):1093–113.
9. Han Z, Wu J, Huang C, Huang Q, Zhao M. A review on sentiment discovery and analysis of educational big-data. Wiley Interdisc Rev Data Min Knowl Disc. 2020;10(1):1–22.
10. Poria S, Cambria E, Bajpai R, Hussain A. A review of affective computing: from unimodal analysis to multimodal fusion. Inform Fusion. 2017;37:98–125.
11. Hollenstein N, Rotsztejn J, Troendle M, Pedroni A, Zhang C, Langer N. ZuCo, a simultaneous EEG and eye-tracking resource for natural sentence reading. Sci Data. 2018;5(1):1–13.
12. Mishra A, Kanojia D, Nagar S, Dey K, Bhattacharyya P. Leveraging cognitive features for sentiment analysis. Proceedings of the 20th SIGNLL conference on computational natural language learning; 2016. p. 156 –166.
13. Liu Q, Wu R, Chen E, Xu G, Su Y, Chen Z, et al. Fuzzy cognitive diagnosis for modelling examinee performance. ACM Trans Intell Syst Technol. 2018;9(4):1–26.
14. Long Y, Xiang R, Lu Q, Huang C-R, Li M. Improving attention model based on cognition grounded data for sentiment analysis. IEEE Trans Affect Comput. 2019:1–14.
15. Long Y, Lu Q, Xiang R, Li M, Huang C R. A cognition based attention model for sentiment analysis. Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing; 2017. p. 462–471.
16. Mishra A, Bhattacharyya P. Automatic extraction of cognitive features from gaze data. Cognitively Inspired Natural Language Processing: Springer; 2018. p. 153–69.
17. Xing FZ, Pallucchini F, Cambria E. Cognitive-inspired domain adaptation of sentiment lexicons. Inf Process Manag. 2019;56(3):554–64.
18. Zupic I, Čater T. Bibliometric methods in management and organization. Organ Res Methods. 2015;18(3):429–72.
19. Piryani R, Madhavi D, Singh VK. Analytical mapping of opinion mining and sentiment analysis research during 2000–2015. Inf Process Manag. 2017;53(1):122–50.
20. Keramatfar A, Amirkhani H. Bibliometrics of sentiment analysis literature. J Inf Sci. 2019;45(1):3–15.
21. Mäntylä MV, Graziotin D, Kuutila M. The evolution of sentiment analysis—a review of research topics, venues, and top cited papers. Comput Sci Rev. 2018;27:16–32.
22. Ahlgren O. Research on sentiment analysis: the first decade. 2016 IEEE 16th International Conference on Data Mining Workshops (ICDMW): IEEE; 2016. p. 890–899.
23. Tubishat M, Idris N, Abushariah MA. Implicit aspect extraction in sentiment analysis: review, taxonomy, opportunities, and open challenges. Inf Process Manag. 2018;54(4):545–63.
24. Zhang D, Wu C, Liu J. Ranking products with online reviews: a novel method based on hesitant fuzzy set and sentiment word framework. J Oper Res Soc. 2020;71(3):528–42.
25. Zhou X, Tao X, Rahman MM, Zhang J. Coupling topic modelling in opinion mining for social media analysis. Proc Int Conf Web Intell. 2017:533–40.
26. Tao X, Zhou X, Zhang J, Yong J. Sentiment analysis for depression detection on social networks. International Conference on Advanced Data Mining and Applications: Springer; 2016. p. 807–810.
27. Liu Z, Liu S, Liu L, Sun J, Peng X, Wang T. Sentiment recognition of online course reviews using multi-swarm optimization-based selected features. Neurocomputing. 2016;185:11–20.
28. Al-Moslmi T, Albared M, Al-Shabi A, Omar N, Abdullah S. Arabic senti-lexicon: constructing publicly available language resources for Arabic sentiment analysis. J Inf Sci. 2018;44(3):345–62.
29. Wu F, Huang Y, Song Y. Structured microblog sentiment classification via social context regularization. Neurocomputing. 2016;175:599–609.
30. Al-Moslmi T, Omar N, Abdullah S, Albared M. Approaches to cross-domain sentiment analysis: a systematic literature review. IEEE Access. 2017;5:16173–92.
31. Kang M, Ahn J, Lee K. Opinion mining using ensemble text hidden Markov models for text classification. Expert Syst Appl. 2018;94:218–27.
32. Calefato F, Lanubile F, Maiorano F, Novielli N. Sentiment polarity detection for software development. Empir Softw Eng. 2018;23(3):1352–82.
33. Li Y, Pan Q, Wang S, Yang T, Cambria E. A generative model for category text generation. Inf Sci. 2018;450:301–15.
34. Zhang Z, Zou Y, Gan C. Textual sentiment analysis via three different attention convolutional neural networks and cross-modality consistent regression. Neurocomputing. 2018;275:1407–15.
35. García-Pablos A, Cuadros M, Rigau G. W2VLDA: almost unsupervised system for aspect based sentiment analysis. Expert Syst Appl. 2018;91:127–37.
36. Jianqiang Z, Xiaolin G, Xuejun Z. Deep convolution neural networks for twitter sentiment analysis. IEEE Access. 2018;6:23253–60.
37. Hassan A, Mahmood A. Convolutional recurrent deep learning model for sentence classification. IEEE Access. 2018;6:13949–57.

38. Arif MH, Li J, Iqbal M, Liu K. Sentiment analysis and spam detection in short informal text using learning classifier systems. Soft Comput. 2018;22(21):7281–91.
39. Dashtipour K, Gogate M, Li J, Jiang F, Kong B, Hussain A. A hybrid Persian sentiment analysis framework: integrating dependency grammar based rules and deep neural networks. Neurocomputing. 2020;380:1–10.
40. Bahassine S, Madani A, Al-Sarem M, Kissi M. Feature selection using an improved Chi-square for Arabic text classification. J King Saud Univ Comp & Info Sci. 2020;32(2):225–31.
41. Song M, Park H, Shin K. Attention-based long short-term memory network using sentiment lexicon embedding for aspect-level sentiment analysis in Korean. Inf Process Manag. 2019;56(3):637–53.
42. Dragoni M, Poria S, Cambria E. OntoSenticNet: a commonsense ontology for sentiment analysis. IEEE Intell Syst. 2018;33(3):77–85.
43. Yang Q, Rao Y, Xie H, Wang J, Wang FL, Chan WH, et al. Segment-level joint topic-sentiment model for online review analysis. IEEE Intell Syst. 2019;34(1):43–50.
44. Kumar A, Sebastian TM. Sentiment analysis: a perspective on its past, present and future. Int J Intell Syst Appl. 2012;4(10):1–14.
45. Serrano-Guerrero J, Olivas JA, Romero FP, Herrera-Viedma E. Sentiment analysis: a review and comparative analysis of web services. Inf Sci. 2015;311:18–38.
46. Cambria E, Poria S, Gelbukh A, Thelwall M. Sentiment analysis is a big suitcase. IEEE Intell Syst. 2017;32(6):74–80.
47. Li X, Rao Y, Xie H, Liu X, Wong T-L, Wang FL. Social emotion classification based on noise-aware training. Data Knowl Eng. 2019;123:101605.
48. Liang W, Xie H, Rao Y, Lau RY, Wang FL. Universal affective model for readers' emotion classification over short texts. Expert Syst Appl. 2018;114:322–33.
49. Li X, Rao Y, Xie H, Lau RYK, Yin J, Wang FL. Bootstrapping social emotion classification with semantically rich hybrid neural networks. IEEE Trans Affect Comput. 2017;8(4):428–42.
50. Rao Y, Xie H, Li J, Jin F, Wang FL, Li Q. Social emotion classification of short text via topic-level maximum entropy model. Inf Manag. 2016;53(8):978–86.
51. Taj S, Shaikh BB, Meghji AF. Sentiment analysis of news articles: a lexicon based approach. 2019 2nd International Conference on Computing, Mathematics and Engineering Technologies (iCoMET): IEEE; 2019. p. 1–5.
52. Ilic S, Marrese-Taylor E, Balazs J, Matsuo Y. Deep contextualized word representations for detecting sarcasm and irony. Proceedings of the 9th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis; 2018. p. 2–7.
53. Burgers C, de Lavalette KYR, Steen GJ. Metaphor, hyperbole, and irony: uses in isolation and in combination in written discourse. J Pragmat. 2018;127:71–83.
54. Kim K, Lee J. Sentiment visualization and classification via semi-supervised nonlinear dimensionality reduction. Pattern Recogn. 2014;47(2):758–68.
55. Rambocas M, Pacheco BG. Online sentiment analysis in marketing research: a review. J Res Interact Mark. 2018;12(2):146–63.
56. Contratres FG, Alves-Souza SN, Filgueiras LVL, DeSouza LS. Sentiment analysis of social network data for cold-start relief in recommender systems. World Conference on Information Systems and Technologies: Springer; 2018. p. 122–132.
57. Li X, Xie H, Song Y, Zhu S, Li Q, Wang FL. Does summarization help stock prediction? A news impact analysis. IEEE Intell Syst. 2015;30(3):26–34.
58. Li X, Xie H, Wang R, Cai Y, Cao J, Wang F, et al. Empirical analysis: stock market prediction via extreme learning machine. Neural Comput & Applic. 2016;27(1):67–78.
59. Seifollahi S, Shajari M. Word sense disambiguation application in sentiment analysis of news headlines: an applied approach to FOREX market prediction. J Intell Inf Syst. 2019;52(1):57–83.
60. Li X, Xie H, Chen L, Wang J, Deng X. News impact on stock price return via sentiment analysis. Knowl-Based Syst. 2014;69:14–23.
61. Alaei AR, Becken S, Stantic B. Sentiment analysis in tourism: capitalizing on big data. J Travel Res. 2019;58(2):175–91.
62. Kiritchenko S, Zhu X, Mohammad SM. Sentiment analysis of short informal texts. J Artif Intell Res. 2014;50:723–62.
63. Nandal N, Tanwar R, Pruthi J. Machine learning based aspect level sentiment analysis for Amazon products. Spat Inf Res. 2020:1–7.
64. Jiménez-Zafra SM, Taulé M, Martín-Valdivia MT, Ureña-López LA, Martí MA. SFU review SP-NEG: a Spanish corpus annotated with negation for sentiment analysis. A typology of negation patterns. Lang Resour Eval. 2018;52(2):533–69.
65. El Alaoui I, Gahi Y, Messoussi R, Chaabi Y, Todoskoff A, Kobi A. A novel adaptable approach for sentiment analysis on big social data. J Big Data. 2018;5(1):12–30.
66. Dandannavar P, Mangalwede S, Deshpande S. Emoticons and their effects on sentiment analysis of Twitter data. EAI International Conference on Big Data Innovation for Sustainable Cognitive Computing: Springer; 2020. p. 191–201.
67. Peng Q, Zhong M. Detecting spam review through sentiment analysis. JSW. 2014;9(8):2065–72.
68. Guzman E, Maalej W. How do users like this feature? A fine grained sentiment analysis of app reviews. 2014 IEEE 22nd International Requirements Engineering Conference (RE): IEEE; 2014. p. 153–162.
69. Batistič S, van der Laken P. History, evolution and future of big data and analytics: a bibliometric analysis of its relationship to performance in organizations. Br J Manag. 2019;30(2):229–51.
70. Peng B, Guo D, Qiao H, Yang Q, Zhang B, Hayat T, et al. Bibliometric and visualized analysis of China's coal research 2000-2015. J Clean Prod. 2018;197:1177–89.
71. Song Y, Chen X, Hao T, Liu Z, Lan Z. Exploring two decades of research on classroom dialogue by using bibliometric analysis. Comput Educ. 2019;137:12–31.
72. Martinho VJPD. Best management practices from agricultural economics: mitigating air, soil and water pollution. Sci Total Environ. 2019;688:346–60.
73. Jiang Y, Ritchie BW, Benckendorff P. Bibliometric visualisation: an application in tourism crisis and disaster management research. Curr Issue Tour. 2019;22(16):1925–57.
74. Pang R, Zhang X. Achieving environmental sustainability in manufacture: a 28-year bibliometric cartography of green manufacturing research. J Clean Prod. 2019;233:84–99.
75. Chen X, Wang S, Tang Y, Hao T. A bibliometric analysis of event detection in social media. Online Inf Rev. 2019;43(1):29–52.
76. Chen X, Lun Y, Yan J, Hao T, Weng H. Discovering thematic change and evolution of utilizing social media for healthcare research. BMC Med Inform Decis Making. 2019;19(2):39–53.
77. Chen X, Liu Z, Wei L, Yan J, Hao T, Ding R. A comparative quantitative study of utilizing artificial intelligence on electronic health records in the USA and China during 2008-2017. BMC Med Inform Decis Making. 2018;18(5):55–69.
78. Hao T, Chen X, Li G, Yan J. A bibliometric analysis of text mining in medical research. Soft Comput. 2018;22(23):7875–92.
79. Chen X, Xie H, Wang FL, Liu Z, Xu J, Hao T. A bibliometric analysis of natural language processing in medical research. BMC Med Inform Decis Making. 2018;18(1):1–14.
80. Chen X, Zhang X, Xie H, Wang FL, Yan J, Hao T. Trends and features of human brain research using artificial intelligence techniques: a bibliometric approach. International Workshop on

Human Brain and Artificial Intelligence: Springer; 2019. p. 69–83.
81. Chen X, Xie H, Cheng G, Poon LK, Leng M, Wang FL. Trends and features of the applications of natural language processing techniques for clinical trials text analysis. Appl Sci. 2020;10(6):2157.
82. Chen X, Zou D, Xie H. Fifty years of British Journal of Educational Technology: a topic modeling based bibliometric perspective. Br J Educ Technol. 2020:1–17.
83. Roberts ME, Stewart BM, Tingley D, Lucas C, Leder-Luis J, Gadarian SK, et al. Structural topic models for open-ended survey responses. Am J Polit Sci. 2014;58(4):1064–82.
84. Bennett R, Vijaygopal R, Kottasz R. Attitudes towards autonomous vehicles among people with physical disabilities. Transp Res A Policy Pract. 2019;127:1–17.
85. Garcia-Rudolph A, Laxe S, Saurí J, Guitart MB. Stroke survivors on Twitter: sentiment and topic analysis from a gender perspective. J Med Internet Res. 2019;21(8):e14077.
86. Hsu A, Brandt J, Widerberg O, Chan S, Weinfurter A. Exploring links between national climate strategies and non-state and subnational climate action in nationally determined contributions (NDCs). Clim Pol. 2020;20(4):443–57.
87. Korfiatis N, Stamolampros P, Kourouthanassis P, Sagiadinos V. Measuring service quality from unstructured data: a topic modeling application on airline passengers' online reviews. Expert Syst Appl. 2019;116:472–86.
88. Chandelier M, Steuckardt A, Mathevet R, Diwersy S, Gimenez O. Content analysis of newspaper coverage of wolf recolonization in France using structural topic modeling. Biol Conserv. 2018;220:254–61.
89. Chen X, Yu G, Cheng G, Hao T. Research topics, author profiles, and collaboration networks in the top-ranked journal on educational technology over the past 40 years: a bibliometric analysis. J Comput Educ. 2019;6(4):563–85.
90. Chen X, Zou D, Cheng G, Xie H. Detecting latent topics and trends in educational technologies over four decades using structural topic modeling: a retrospective of all volumes of Computers & Education. Comput Educ. 2020;151:1–53.
91. Rothschild JE, Howat AJ, Shafranek RM, Busby EC. Pigeonholing partisans: stereotypes of party supporters and partisan polarization. Polit Behav. 2019;41(2):423–43.
92. Chen X, Chen J, Cheng G, Gong T. Topics and trends in artificial intelligence assisted human brain research. PLoS One. 2020;15(4):e0231192.
93. Roberts ME, Stewart BM, Tingley D. Stm: R package for structural topic models. J Stat Softw. 2014;10(2):1–40.
94. Jiang H, Qiang M, Lin P. A topic modeling based bibliometric exploration of hydropower research. Renew Sust Energ Rev. 2016;57:226–37.
95. Farrell J. Corporate funding and ideological polarization about climate change. Proc Natl Acad Sci USA. 2016;113(1):92–7.
96. Tvinnereim E, Fløttum K. Explaining topic prevalence in answers to open-ended survey questions about climate change. Nat Clim Chang. 2015;5(8):744–7.
97. Jiang H, Qiang M, Fan Q, Zhang M. Scientific research driven by large-scale infrastructure projects: a case study of the Three Gorges Project in China. Technol Forecast Soc Chang. 2018;134:61–71.
98. Mann HB. Nonparametric tests against trend. Econometrica J Econ Soc. 1945;13:245–59.
99. Chen X, Hao T. Quantifying and visualizing the research status of social media and health research field. Social Web and Health Research: Springer; 2019. p. 31–51.
100. Hirsch JE, Buela-Casal G. The meaning of the h-index. Int J Clin Health Psychol. 2014;14(2):161–4.
101. Liu B. Sentiment analysis: mining opinions, sentiments, and emotions: Cambridge University Press; 2015. p. 8.
102. Zhao Y, Qin B, Liu T. Exploiting syntactic and semantic kernels for target-polarity word collocation extraction. 2018 First Asian Conference on Affective Computing and Intelligent Interaction (ACII Asia): IEEE; 2018. p. 1–6.
103. He J, Song T, Peng W, Sheng Q, Song J. Automatic acquisition of matching patterns for pattern-based parsing on specific Chinese text. 2016 IEEE/WIC/ACM International Conference on Web Intelligence Workshops (WIW): IEEE; 2016. p. 17–20.
104. Xiong S, Ji D. Exploiting capacity-constrained k-means clustering for aspect-phrase grouping. International Conference on Knowledge Science, Engineering and Management: Springer; 2015. p. 370–381.
105. Araque O, Zhu G, García-Amado M, Iglesias CA. Mining the opinionated web: classification and detection of aspect contexts for aspect based sentiment analysis. 2016 IEEE 16th International Conference on Data Mining Workshops (ICDMW): IEEE; 2016. p. 900–907.
106. Chen G, Zhang Q, Chen D. A pair-wise method for aspect-based sentiment analysis. International Conference on Cognitive Computing: Springer; 2018. p. 18–29.
107. Qasem M, Thulasiraman P, Thulasiram RK. Constrained ant brood clustering algorithm with adaptive radius: a case study on aspect based sentiment analysis. 2017 IEEE Symposium Series on Computational Intelligence (SSCI): IEEE; 2017. p. 1–8.
108. Omurca Sİ, Ekinci E. Using adjusted Laplace smoothing to extract implicit aspects from Turkish hotel reviews. 2018 Innovations in Intelligent Systems and Applications (INISTA): IEEE; 2018.p. 1–6.
109. Singh JP, Irani S, Rana NP, Dwivedi YK, Saumya S, Roy PK. Predicting the "helpfulness" of online consumer reviews. J Bus Res. 2017;70:346–55.
110. Liang T-P, Li X, Yang C-T, Wang M. What in consumer reviews affects the sales of mobile apps: a multifacet sentiment analysis approach. Int J Electron Commer. 2015;20(2):236–60.
111. Garg P, Garg H, Ranga V. Sentiment analysis of the Uri terror attack using Twitter. 2017 International Conference on Computing, Communication and Automation (ICCCA): IEEE; 2017. p. 17–20.
112. Han S, Kavuluru R. On assessing the sentiment of general tweets. Canadian Conference on Artificial Intelligence: Springer; 2015. p. 181–195.
113. Raja M, Swamynathan S. Tweet sentiment analyzer: sentiment score estimation method for assessing the value of opinions in tweets. Proceedings of the International Conference on Advances in Information Communication Technology & Computing: ACM; 2016. p. 1–6.
114. Gul S, Mahajan I, Nisa NT, Shah TA, Asifa J, Ahmad S. Tweets speak louder than leaders and masses: an analysis of tweets about the Jammu and Kashmir elections 2014. Online Inf Rev. 2016;40(7):900–12.
115. Singh P, Sawhney RS, Kahlon KS. Predicting the outcome of Spanish general elections 2016 using Twitter as a tool. International Conference on Advanced Informatics for Computing Research: Springer; 2017. p. 73–83.
116. Dinkić N, Džaković N, Joković J, Stoimenov L, Đukić A. Using sentiment analysis of Twitter data for determining popularity of city locations. International Conference on ICT Innovations: Springer; 2016. p. 156–164.
117. Purnamasari PD, Taqiyuddin M, Ratna AAP. Performance comparison of text-based sentiment analysis using recurrent neural network and convolutional neural network. Proceedings of the 3rd International Conference on Communication and Information Processing: ACM; 2017. p. 19–23.

118. Huang Q, Chen R, Zheng X, Dong Z. Deep sentiment representation based on CNN and LSTM. 2017 International Conference on Green Informatics (ICGI): IEEE; 2017. p. 30–33.
119. Kuta M, Morawiec M, Kitowski J. Sentiment analysis with tree-structured gated recurrent units. International Conference on Text, Speech, and Dialogue: Springer; 2017. p. 74–82.
120. Huang M, Xie H, Rao Y, Feng J, Wang FL. Sentiment strength detection with a context-dependent lexicon-based convolutional neural network. Inf Sci. 2020;520:389–99.
121. Sato M, Orihara R, Sei Y, Tahara Y, Ohsuga A. Text classification and transfer learning based on character-level deep convolutional neural networks. International Conference on Agents and Artificial Intelligence: Springer; 2017. p. 62–81.
122. Bodrunova SS, Blekanov IS, Kukarkin M, Zhuravleva N. Negative a/effect: sentiment of French-speaking users and its impact upon affective hashtags on Charlie Hebdo. International Conference on Internet Science: Springer; 2018. p. 226–241.
123. Chen X, Qin Z, Zhang Y, Xu T. Learning to rank features for recommendation over multiple categories. Proceedings of the 39th International ACM SIGIR Conference on Research and Development in Information Retrieval:ACM; 2016. p. 305–314.
124. Chen S, Huang Y, Huang W. Big data analytics on aviation social media: the case of china southern airlines on sina weibo. 2016 IEEE Second International Conference on Big Data Computing Service and Applications (BigDataService): IEEE; 2016. p. 152–155.
125. Yun Y, Hooshyar D, Jo J, Lim H. Developing a hybrid collaborative filtering recommendation system with opinion mining on purchase review. J Inf Sci. 2018;44(3):331–44.
126. Yan Q, Zhou S, Wu S. The influences of tourists' emotions on the selection of electronic word of mouth platforms. Tour Manag. 2018;66:348–63.
127. Jayaratna MSH, Bouguettaya A, Dong H, Qin K, Erradi A. Subjective evaluation of market-driven cloud services. 2017 IEEE International Conference on Web Services (ICWS): IEEE; 2017. p. 516–523.
128. López MB, Alor-Hernández G, Sánchez-Cervantes JL, del Pilar S-ZM, Paredes-Valverde MA. EduRP: an educational resources platform based on opinion mining and semantic web. J Univ Comput Sci. 2018;24(11):1515–35.
129. Esparza GG, de Luna A, Zezzatti AO, Hernandez A, Ponce J, Álvarez M, et al. A sentiment analysis model to analyze students reviews of teacher performance using support vector machines. International Symposium on Distributed Computing and Artificial Intelligence: Springer; 2017. p. 157–164.
130. Chauhan GS, Agrawal P, Meena YK. Aspect-based sentiment analysis of students' feedback to improve teaching–learning process. Information and Communication Technology for Intelligent Systems: Springer; 2019. p. 259–66.
131. de Paula Santos F, Lechugo CP, Silveira-Mackenzie IF. "Speak well" or "complain" about your teacher: a contribution of education data mining in the evaluation of teaching practices. 2016 International Symposium on Computers in Education (SIIE): IEEE; 2016. p. 1–4.
132. Maqsood H, Mehmood I, Maqsood M, Yasir M, Afzal S, Aadil F, et al. A local and global event sentiment based efficient stock exchange forecasting using deep learning. Int J Inf Manag. 2020;50:432–51.
133. García-Díaz V, Espada JP, Crespo RG, G-Bustelo BCP, Lovelle JMC. An approach to improve the accuracy of probabilistic classifiers for decision support systems in sentiment analysis. Appl Soft Comput. 2018;67:822–33.
134. Ma R, Wang K, Qiu T, Sangaiah AK, Lin D, Liaqat HB. Feature-based compositing memory networks for aspect-based sentiment classification in social internet of things. Futur Gener Comput Syst. 2019;92:879–88.
135. Jabreel M, Moreno A. A deep learning-based approach for multi-label emotion classification in tweets. Appl Sci. 2019;9(6):1123–39.
136. Poria S, Majumder N, Hazarika D, Cambria E, Gelbukh A, Hussain A. Multimodal sentiment analysis: addressing key issues and setting up the baselines. IEEE Intell Syst. 2018;33(6):17–25.
137. Sun M, Konstantelos I, Strbac G. A deep learning-based feature extraction framework for system security assessment. IEEE Trans Smart Grid. 2018;10(5):5007–20.
138. Valdivia A, Martínez-Cámara E, Chaturvedi I, Luzón MV, Cambria E, Ong YS, et al. What do people think about this monument? Understanding negative reviews via deep learning, clustering and descriptive rules. J Ambient Intell Humaniz Comput. 2020;11(1):39–52.
139. Ma Y, Peng H, Cambria E. Targeted aspect-based sentiment analysis via embedding commonsense knowledge into an attentive LSTM. Thirty-second AAAI Conference on Artificial Intelligence; 2018. p. 5876–5883.
140. Majumder N, Poria S, Hazarika D, Mihalcea R, Gelbukh A, Cambria E. Dialoguernn: an attentive RNN for emotion detection in conversations. Proc AAAI Conf Artif Intell. 2019;33:6818–25.
141. Zhao W, Peng H, Eger S, Cambria E, Yang M. Towards scalable and reliable capsule networks for challenging NLP applications. Proceedings of the 57th annual meeting of the Association for Computational Linguistics; 2019. p. 1549–1559.
142. Peng H, Ma Y, Li Y, Cambria E. Learning multi-grained aspect target sequence for Chinese sentiment analysis. Knowl-Based Syst. 2018;148:167–76.
143. Majumder N, Poria S, Gelbukh A, Akhtar MS, Cambria E, Ekbal A. IARM: inter-aspect relation modeling with memory networks in aspect-based sentiment analysis. Proceedings of the 2018 conference on Empirical Methods in Natural Language Processing; 2018. p. 3402–3411.
144. Al-Smadi M, Al-Ayyoub M, Jararweh Y, Qawasmeh O. Enhancing aspect-based sentiment analysis of Arabic hotels' reviews using morphological, syntactic and semantic features. Inf Process Manag. 2019;56(2):308–19.