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A Decade of Sentic Computing: Topic Modeling and Bibliometric Analysis

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Abstract

Research on sentic computing has received intensive attention in recent years, as indicated by the increased availability of academic literature. However, despite the growth in literature and researchers' interests, there are no reviews on this topic. This study comprehensively explores the current research progress and tendencies, particularly the thematic structure of sentic computing, to provide insights into the issues addressed during the past decade and the potential future of sentic computing. We combined bibliometric analysis and structural topic modeling to examine sentic computing literature in various aspects, including the tendency of annual article count, top journals, countries/regions, institutions, and authors, the scientific collaborations between major contributors, as well as the major topics and their tendencies. We obtained interesting and meaningful findings. For example, sentic computing has attracted growing interest in academia. In addition, *Cognitive Computation* and *Nanyang Technological University* were found to be the most productive journal and institution in publishing sentic computing studies, respectively. Moreover, important issues such as *cyber issues and public opinion*, *deep neural networks and personality*, *financial applications and user profiles*, and *affective and emotional computing* have been commonly addressed by authors focusing on sentic computing. Our study provides a thorough overview of sentic computing, reveals major concerns among scholars during the past decade, and offers insights into the future directions of sentic computing research.

Keywords Sentic computing · Bibliometric analysis · Structural topic modeling · Topic detection and evolution analysis

Introduction

Sentic computing [1] is a multi-disciplinary research field that focuses on sentiment analysis at the intersection between affective and common sense computing and allows text analysis at various levels, such as documents, sentences, and concepts [2]. The term "sentic computing," coined by Erik Cambria and Amir Hussain in 2010, was derived from the Latin words "sensus" and "sentire." As a field originated from natural language processing (NLP) or text-based analysis, sentic computing is not a common term for researchers working with modalities such as vocal or facial expressions, physiology, and affect. Specifically, sentic computing is proposed to address issues within NLP (e.g., dependency, consistency, and transparency) by adopting a multi-disciplinary technique to bridge the gap between statistical NLP and various necessary disciplines to achieve a better understanding of human languages. Sentiment analysis is closely related to sentic computing, as it aims to facilitate the understanding and classification of subjectivity within various sources like product reviews [3]. However, sentic

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computing infers polarity from a text by analyzing knowledge-based linguistic patterns and taking advantage of statistical algorithms [4], whereas sentiment analysis is a computational study of opinions, sentiments, and emotions [5]. In this sense, sentic computing can be regarded as a computing technique utilized to realize the purpose of sentiment analysis. Sentic computing has received increasing attention in academia because of the recent advances in artificial intelligence [6, 7].

During the past decade, sentic computing has been used in various applications ranging from healthcare quality assessment to dialogue systems in daily life [8, 9]. As a common sense knowledge base in sentic computing, SenticNet [10] uses common sense knowledge to facilitate the transmission of conceptual and affective information within the natural language to machines. Research on sentic computing has demonstrated its popularity and wide impact among scholars with a growing number of scientific literature available.

With the increasing volume of sentic computing studies, there is a need to conduct a review to better comprehend the research status and development tendencies of this area. According to our survey on the available literature, currently, no review particularly focuses on sentic computing. However, there are many reviews available on relevant topics, most of which were conducted using systematic analysis methods (see Table 1).

Thus, to fill the research gap, this study is conducted targeting existing sentic computing literature. In the field of literature review, in addition to methodologies such as systematic review analysis and meta-analysis that require considerable manual coding effort, bibliometric analysis has been increasingly used as it overcomes limitations of manual methods (e.g., the limited number of reviewed papers, as well as error-provoking and time-consuming issues). Particularly, bibliometrics has been widely adopted in different research fields [19–22]. Keramatfar and Amirkhani [23] used bibliometrics to analyze studies concerning sentiment analysis and examine research tendencies. They found that the term "sentiment analysis" was more acceptable than "opinion mining." In addition, Twitter and support vector machine (SVM) were the most popular social network and classification technique for sentiment analysis, respectively. Mäntylä et al. [24] adopted text mining and manual coding methods to analyze 6996 articles regarding sentiment analysis. The wide application of bibliometric analysis has proven its effectiveness in providing a thorough overview of a particular research field. Therefore, bibliometrics is suitable to explore the status and tendencies of sentic computing research. In addition, to further depict the thematic structure of this field, we combined bibliometrics with an advanced NLP technique named topic modeling. Topic models are commonly adopted to "discover the hidden thematic structure in large archives of documents (p. 1) [25]." Structural topic modeling (STM), built on latent Dirichlet allocation (LDA) [26], was proposed to allow scholars to discover topics and estimate their relationship to document metadata. In recent years, LDA and STM have been

Table 1 Examples of reviews on topics related to sentic computing

Author(s) and year	Research aims	Methods	Analysis aspects or research questions
Mehta et al. (2019) [11]	To review significant machine learning approaches used to detect personality	Systematic review	The most popular methods for automatic personality detection, different computational data sets, and major machine learning algorithms for personality detection
Boudad et al. (2018) [12]	To review major studies that addressed Arabic sentiment analysis (ASA)	Systematic review	Linguistic characteristics of standard Arabic, challenges of ASA, and essential studies concerning ASA
Wang et al. (2020) [13]	To review and discuss current emotion categorization approaches for emotion analysis	Systematic review	Based on categories of social science, computing science, and engineering
Kumar and Jaiswal (2020) [14]	To explore the feasibility, scope, and relevance of Twitter sentiment analysis based on soft computing	Systematic review	Relevant journals, commonly used datasets and domains, the most frequently used soft computing techniques, commonly adopted performance metrics, as well as tendencies and impact
Sukthanker et al. (2020) [15]	To clarify the scope of anaphora and coreference resolution	Systematic review	Data sets, evaluation metrics, and research approaches
Zhang et al. (2020) [16]	To present an overview of emotion recognition with the use of multi-modal data and machine learning techniques	Systematic review	Physiological data labeling methods, as well as different feature extraction and feature dimensionality reduction approaches
Ain et al. (2019) [17]	To review deep learning techniques for sentiment analysis	Systematic review	Model used, purpose, data set, and results
Azmi et al. (2019) [18]	To survey computational and NLP-based studies of hadith literature	Systematic review	From the perspectives of hadith content and narration

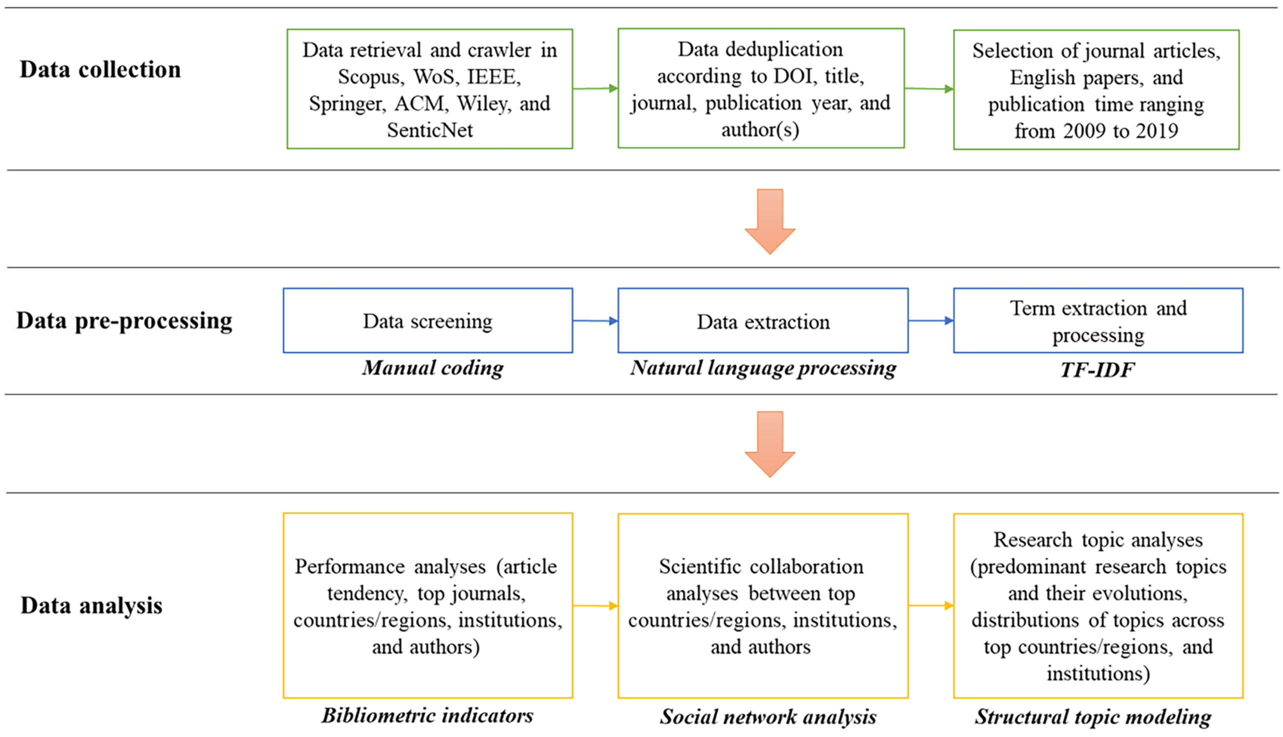


Fig. 1 Methodological framework for data collection and analyses

adopted in various domains such as customer review [27–29], literature [19, 30], and open-survey questionnaire analyses [31].

To that end, by adopting bibliometrics and STM, we aim to explore the academic literature on sentic computing. There are five research questions:

RQ1: What was the tendency of the number of relevant publications on a year-by-year basis?
RQ2: What were the top journals, countries/regions, institutions, and authors?
RQ3: What were the scientific collaborations between major countries/regions, institutions, and authors?
RQ4: What were the major topics and how did they evolve?
RQ5: What were the topic distributions of major journals, countries/regions, institutions, and authors?

Data and Methods

The methodological framework for data collection and analyses is depicted in Fig. 1, including data collection, data preprocessing, and data analyses.

Data Collection

This study examined one decade of sentic computing studies starting from 2010 when the term "sentic computing" was initially coined [32]. Several commonly used databases, including Web of Science, Scopus, Association for Computing Machinery, Springer, IEEE Xplore Digital Library, and Wiley, were used to search sentic computing studies using the search term "sentic*" to find correspondences in title, abstract, or keywords of each article. In addition, relevant publications mentioned in the active series, as well as those accepted by the special issues listed in SenticNet[1] were also included. Data deduplication was applied by examining article information such as digital object identifier, title, publication source, publication year, and author(s) to delete duplicated ones. Furthermore, we restricted the reviewing scope to journal articles that were written in English and published from 2009 to 2019.

Data Preprocessing

For the remaining records, a filtering process was conducted by two domain experts in sentic computing to exclude the articles that were not closely relevant to the topic. Detailed criteria listed in Table 2 were proposed to facilitate the filtering. In the table, the second column presents the prerequisites. Thus, studies meeting any of the inclusion criteria were closely related to the field of NLP, whereas studies meeting any of the exclusion criteria were relevant to non-NLP and

[1] https://sentic.net/

Table 2 Inclusion and exclusion criteria

Inclusion criteria	NLP	I-1	Emotional polarity analysis and classification
		I-2	Public's opinion on particular issues or products
		I-3	Emotional scoring
		I-4	Semantic feature extraction for sentiment analysis
		I-5	Aspect extraction
		I-6	Techniques or algorithms development for sentiment analysis and opinion mining
Exclusion criteria	Non-NLP and multi-modality data	E-1	Physical emotion detection and medical classification
		E-2	Affective posture recognition
		E-3	Studies focusing on the analysis and detection of emotions from human facial expressions, physiology, and electrical signals such as electrocardiogram
		E-4	Emotion recognition ability of humans
		E-5	Theory of mind
		E-6	Pure psychological or pharmacological experimental studies

multi-modality data analysis, which is not the focus of the present study. Two domain experts first examined 200 articles individually, resulting in inter-rater reliability of 94%. Inconsistencies were resolved through discussions. Then, they jointly filtered the remaining data. Finally, 308 articles remained for further analysis.

Performance Analyses

Performance analyses involved analyses of the tendency of annual article count, top journals, countries/regions, institutions, and authors. Bibliometric indicators including article count, citation count, Hirsch index (H-index), and average citations per article (ACP) were used. The article and citation counts indicate productivity and influence, respectively [33]. The H-index is popularly adopted to measure academic impact [34]. In addition, ACP is also a commonly adopted impact indicator based on received citations [35]. The citation count, H-index, and ACP of each journal, country/region, institution, and author were calculated based on the Google Scholar[2] citations received by each of the 308 publications.

Scientific Collaboration Analysis

Social network analysis (SNA) visualized scientific relationsin sentic computing research through networks and graph mapping. In this study, SNA was conducted by using an open-source software called Gephi,[3] which generates collaborative networks by indicating authors, institutions, or countries/regions as nodes. Collaborative relations were indicated by lines. The node size and line width were proportional to the article count and collaborative strength. In addition, colors were used to indicate countries/regions or continents.

Research Topics and Tendencies

The major research topics and issues covered within the 308 sentic computing articles were explored using STM. In this study, STM was conducted using *stm* [36]. First, following the strategies in previous studies [37, 38], a series of models were developed, and the results were examined and compared by domain experts to select the model that fitted our data the most. According to the criteria for model selection proposed by Chen et al. [39], an STM model with seven topics was finally selected. The topics were labeled according to the representative terms and articles.

Furthermore, to explore whether each of the identified topics showed statistically significant tendencies during the studied period, a nonparametric Mann–Kendall statistical test, proposed by Mann [40] and Kendall [41], was adopted. In addition, we also explored the topic distributions of the major contributors.

Results

Tendency of Annual Article Count

The tendency of the annual article count is depicted in Fig. 2. The annual numbers of sentic computing literature have overall increased, rising from 1 in 2011 to 80 in 2019. A significant decrease was observed in 2015. The largest number of articles was published in 2019, with a growth rate of 48.15% compared to the previous year. The results indicate that research on sentic computing has attracted growing interest in academia.

[2] https://scholar.google.com/

[3] https://gephi.org/

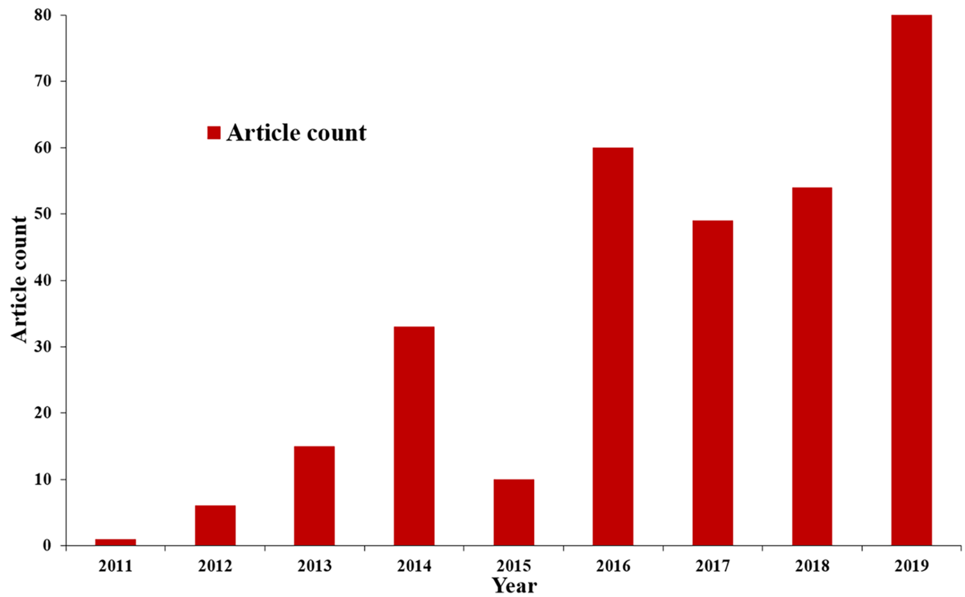


Fig. 2 Tendency of annual article count

Top Research Articles

We identified the top ten impactful research articles based on the number of annual citations (C/Y) [42] and the number of total citations (TC) (Table 3).

Among the top ten articles ranked by C/Y, the most impactful one was by Cambria [4], with a C/Y value of 140.00. This article lists the tasks regarding affective computing and sentiment analysis. The second and third articles were conducted by Poria et al. [43, 44] with C/Y values of 103.25 and 77.00, respectively. Poria et al. proposed the

Table 3 Top sentic computing articles

Top studies ranked by C/Y		
Author(s) and year	Title	C/Y
Cambria (2016) [4]	Affective computing and sentiment analysis	140.00
Poria et al. (2016) [43]	Aspect extraction for opinion mining with a deep convolutional neural network	103.25
Poria et al. (2016) [44]	Fusing audio, visual and textual clues for sentiment analysis from multi-modal content	77.00
Saif et al. (2016) [45]	Contextual semantics for sentiment analysis of Twitter	66.25
Majumder et al. (2017) [46]	Deep learning-based document modeling for personality detection from text	65.00
Kasun et al. (2013) [47]	Representational learning with extreme learning machine for big data	61.43
Poria et al. (2014) [48]	Sentic patterns: dependency-based rules for concept-level sentiment analysis	48.83
Manek et al. (2017) [49]	Aspect term extraction for sentiment analysis in large movie reviews using Gini Index feature selection method and SVM classifier	47.67
Ribeiro et al. (2016) [50]	SentiBench—a benchmark comparison of state-of-the-practice sentiment analysis methods	44.50
Cambria et al. (2017) [51]	Sentiment analysis is a big suitcase	43.33
Top studies ranked by TC		
Author(s) & Year	Title	TC
Cambria (2016) [4]	Affective computing and sentiment analysis	560
Kasun et al. (2013) [47]	Representational learning with extreme learning machine for big data	430
Poria et al. (2016) [43]	Aspect extraction for opinion mining with a deep convolutional neural network	413
Poria et al. (2016) [44]	Fusing audio, visual and textual clues for sentiment analysis from multi-modal content	308
Poria et al. (2014) [48]	Sentic patterns: dependency-based rules for concept-level sentiment analysis	293
Saif et al. (2016) [45]	Contextual semantics for sentiment analysis of Twitter	265
Dinakar et al. (2012) [52]	Common sense reasoning for detection, prevention, and mitigation of cyberbullying	255
Li et al. (2014) [53]	News impact on stock price return via sentiment analysis	229
Majumder et al. (2017) [46]	Deep learning-based document modeling for personality detection from text	195
Wöllmer et al. (2013) [54]	Youtube movie reviews: sentiment analysis in an audio-visual context	182

Table 4 Top journals

Journals	A (R)	H (R)	C (R)	ACP
Cognitive Computation	33 (1)	16 (3)	1079 (3)	32.70
Knowledge-Based Systems	31 (2)	22 (1)	2375 (2)	76.61
IEEE Intelligent Systems	28 (3)	20 (2)	2608 (1)	93.14
IEEE Transactions on Affective Computing	15 (4)	8 (6)	288 (9)	19.20
Information Processing & Management	12 (5)	11 (4)	768 (5)	64.00
Neural Networks	12 (5)	11 (4)	462 (6)	38.50
IEEE Access	11 (7)	4 (11)	71 (21)	6.45
Artificial Intelligence Review	10 (8)	6 (8)	302 (8)	30.20
Natural Language Semantics	10 (8)	5 (10)	113 (17)	11.30
IEEE Computational Intelligence Magazine	9 (10)	7 (7)	1042 (4)	115.78
Multimedia Tools and Applications	9 (10)	6 (8)	159 (14)	17.67

R ranking position, *H* H-index; *A* article count, *C* citation count, *ACP* average citations per article

first deep learning algorithm for aspect extraction and an approach for multi-modal sentiment analysis by using audio, visual, and textual modalities. Seven articles [4, 43–48] are listed in both rankings, indicating their wide impact on sentic computing.

Top Journals, Countries/Regions, Institutions, and Authors

The 308 articles addressing sentic computing were distributed in a total of 91 journals. The top 11 ranked by article count listed in Table 4 contributed to over 58% of the total corpus. *Cognitive Computation* was the most productive journal in the field, with 33 articles, followed by *Knowledge-Based Systems* (31), *IEEE Intelligent Systems* (28), and *IEEE Transactions on Affective Computing* (15). From the perspective of the H-index, the top three were *Knowledge-Based Systems* (an H-index value of 22), *IEEE Intelligent Systems* (20), and *Cognitive Computation* (16). The top three productive journals were also the top three influential ones, indicating the active role and significant influence of these three journals in sentic computing research. In terms of ACP, among the listed journals, the top four were *IEEE Computational Intelligence Magazine* (115.78), *IEEE Intelligent Systems* (93.14), *Knowledge-Based Systems* (76.61), and *Information Processing & Management* (64.00).

There were 50 countries/regions that contributed to the 308 sentic computing articles. The top 12 countries/regions are shown in Table 5. China contributed to over 19% of the corpus, with 60 articles, indicating its active role in the sentic computing research, followed by the USA (48), Singapore (47), and Italy (43). From the perspective of the H-index, the top five were Singapore (an H-index value of 26), the USA (24), China (24), the UK (23), and Italy (21). The top three productive countries/regions were also the top three influential ones, indicating the active role and significant influence of China, the USA, and Singapore in the publication of sentic computing studies. In terms of ACP, among the listed countries/regions, the top five were Mexico (103.40), Singapore (92.36), the USA (59.23), the UK (55.08), and France (51.50).

357 institutions contributed to the publication of the analyzed articles. The top institutions with a minimum value of five articles are listed in Table 6. *Nanyang Technological University* was in the first position for three indicators (i.e., article count, H-index, and citation count), indicating its active role and wide impact in the field of sentic computing, with 40 articles, an H-index value of 22, and 4006 citations. The *University of Stirling* (due to the former affiliation of *Amir Hussain*) was in second position with 17 articles. Other productive institutions included *Massachusetts Institute of Technology* (10), *City University of Hong Kong* (9), and *National Polytechnic Institute* (9). These institutions were also among the top five influential ones, with H-index values of 12, 8, 8, and 7, respectively. Such results highlight the active

Table 5 Top countries/regions

C/R	A (R)	H (R)	C (R)	ACP
China	60 (1)	24 (2)	1828 (4)	30.47
USA	48 (2)	24 (2)	2843 (2)	59.23
Singapore	47 (3)	26 (1)	4341 (1)	92.36
Italy	43 (4)	21 (5)	1652 (5)	38.42
UK	39 (5)	23 (4)	2148 (3)	55.08
India	32 (6)	11 (7)	717 (9)	22.41
Spain	26 (7)	14 (6)	923 (7)	35.50
Hong Kong	15 (8)	11 (7)	694 (10)	46.27
France	14 (9)	8 (9)	721 (8)	51.50
Pakistan	12 (10)	6 (11)	173 (19)	14.42
Canada	11 (11)	5 (15)	125 (23)	11.36
Mexico	10 (12)	7 (10)	1034 (6)	103.40

R ranking position, *H* H-index, *A* article count, *C* citation count, *ACP* average citations per article

Table 6 Top institutions

Institutions	C/R	A (R)	H (R)	C (R)	ACP
Nanyang Technological University	Singapore	40 (1)	22 (1)	4006 (1)	100.15
University of Stirling	UK	17 (2)	12 (2)	1173 (2)	69.00
Massachusetts Institute of Technology	USA	10 (3)	8 (3)	924 (4)	92.40
City University of Hong Kong	Hong Kong	9 (4)	8 (3)	613 (6)	68.11
National Polytechnic Institute	Mexico	9 (4)	7 (5)	1034 (3)	114.89
Fondazione Bruno Kessler	Italy	7 (6)	6 (6)	182 (28)	26.00
Delhi Technological University	India	6 (7)	4 (12)	73 (78)	12.17
Tsinghua University	China	6 (7)	5 (7)	315 (10)	52.50
University of Trento	Italy	6 (7)	5 (7)	210 (21)	35.00
Carnegie Mellon University	USA	5 (10)	4 (12)	220 (20)	44.00
National Research Council	Italy	5 (10)	5 (7)	229 (17)	45.80
Hong Kong Polytechnic University	Hong Kong	5 (10)	3 (19)	67 (81)	13.40
National University of Singapore	Singapore	5 (10)	5 (7)	286 (13)	57.20
University of Cagliari	Italy	5 (10)	5 (7)	50 (107)	10.00
University of Genoa	Italy	5 (10)	3 (19)	82 (66)	16.40
University of Michigan	USA	5 (10)	3 (19)	160 (36)	32.00

R ranking position, *H* H-index, *A* article count, *C* citation count, *ACP* average citations per article

role and wide impact of these institutions in sentic computing research. Regarding ACP, among the listed institutions, the top three were *National Polytechnic Institute* (114.89), *Nanyang Technological University* (100.15), and *Massachusetts Institute of Technology* (92.40).

824 authors contributed to the publication of the analyzed articles. According to the article count, the top authors with a minimum value of five articles are listed in Table 7. *Erik Cambria* from *Nanyang Technological University* was in the first position for three indicators (i.e., article count, H-index, and citation count), indicating his active role and wide impact in the field of sentic computing, with 40 articles, an H-index value of 25, and 4001 citations. *Amir Hussain* from *Edinburgh Napier University* (formerly with the *University of Stirling*) was in second position on the three indicators. Other productive authors included *Soujanya Poria* from *Singapore University of Technology and Design* (11), *Alexander Gelbukh* from *National Polytechnic Institute of Mexico* (9), and *Haoran Xie* from *Lingnan University* (8). These authors were also among the top five influential ones, with H-index values of 13, 10, 7, and 6, respectively. Such results highlight the active role and wide impact of the mentioned authors in the research on sentic computing. From the perspective of ACP, among the listed authors, the top three were *Soujanya Poria* (150.27), *Alexander Gelbukh* (114.89), and *Erik Cambria* (100.03).

Scientific Collaborations

The collaborations between the 50 countries/regions are depicted in Fig. 3. Among the 50 countries/regions, 20 are in Asia, 19 in Europe, 3 in Africa, 3 in North America, 3 in

Table 7 Top authors

Authors	Current institutions	A (R)	H (R)	C (R)	ACP
Erik Cambria	Nanyang Technological University	40 (1)	25 (1)	4001 (1)	100.03
Amir Hussain	Edinburgh Napier University	19 (2)	13 (2)	1207 (3)	63.53
Soujanya Poria	Singapore University of Technology and Design	11 (3)	10 (3)	1653 (2)	150.27
Alexander Gelbukh	National Polytechnic Institute of Mexico	9 (4)	7 (4)	1034 (5)	114.89
Haoran Xie	Lingnan University	8 (5)	6 (5)	446 (7)	55.75
Diego Reforgiato Recupero	University of Cagliari	7 (6)	6 (5)	260 (25)	37.14
Federica Bisio	University of Genoa	6 (7)	4 (8)	101 (104)	16.83
Qing Li	Hong Kong Polytechnic University	6 (7)	5 (7)	259 (29)	43.17
Fu Lee Wang	Open University of Hong Kong	5 (9)	4 (8)	117 (79)	23.40
Rada Mihalcea	University of Michigan	5 (9)	3 (20)	160 (60)	32.00
Raymond Yiu Keung Lau	City University of Hong Kong	5 (9)	4 (8)	223 (38)	44.60
Yanghui Rao	Sun Yat-Sen University	5 (9)	4 (8)	169 (57)	33.80

R ranking position, *H* H-index, *A* article count, *C* citation count, *ACP* average citations per article

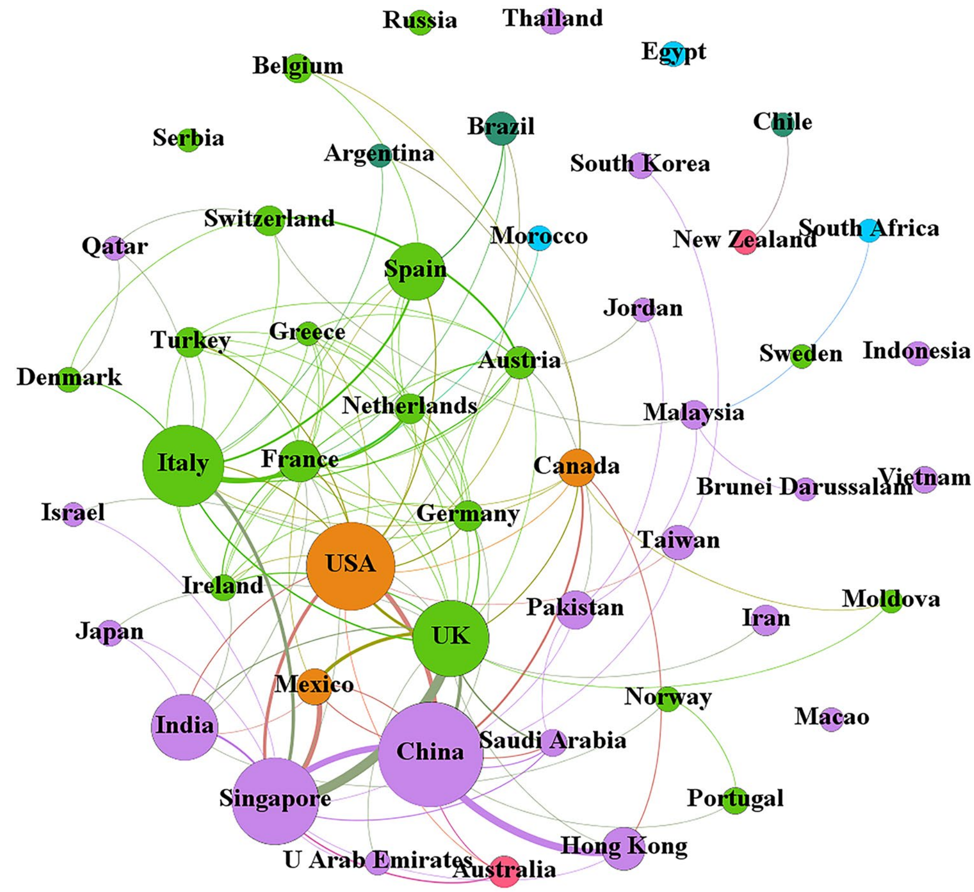


Fig. 3 Collaborative network of countries/regions

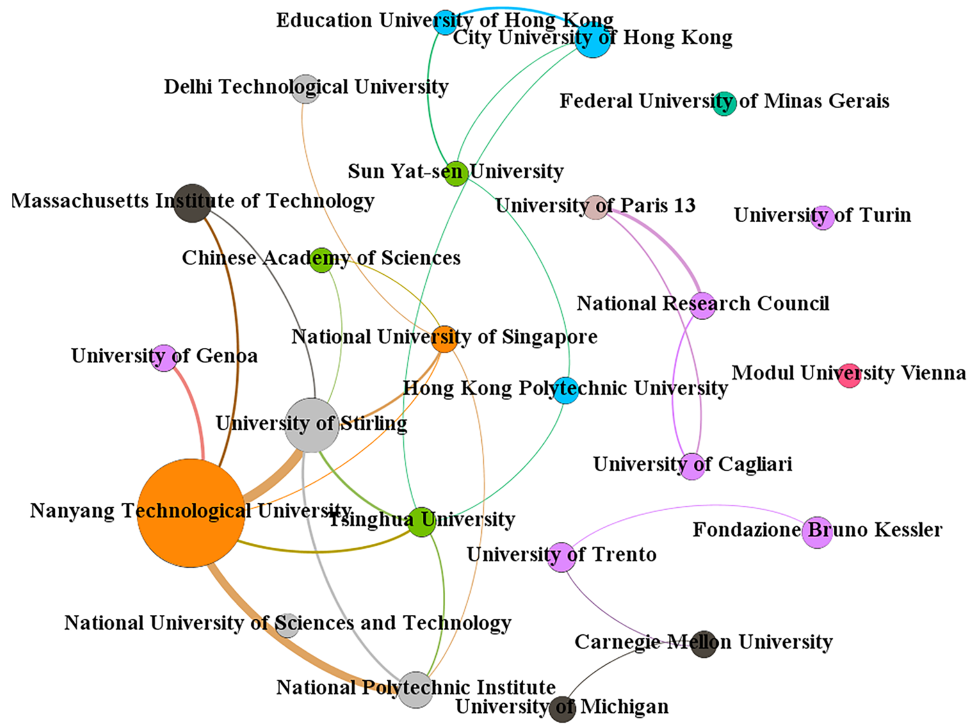
South America, and 2 in Oceania. There was a considerable number of collaborations between countries/regions from Europe and Asia. The UK, the USA, Italy, France, and Singapore were the most collaborative, with 21, 17, 16, 15, and 14 collaborators, respectively. Singapore and the UK collaborated in 17 articles, followed by Hong Kong and China (13), as well as Singapore and China (11).

The collaborations between the top 24 institutions are visulized (Fig. 4). Among the 24 institutions, 6 are in Italy, 3 in China, 3 in Hong Kong, and 3 in the USA. *Nanyang Technological University*, *University of Stirling*, *Tsinghua University*, and *National University of Singapore* were the most collaborative, collaborating with 6, 6, 5, and 5 other institutions, respectively. *University of Stirling* and *Nanyang Technological University* were the closest collaborators, owing to the affiliations of *Amir Hussain* and *Erik Cambria*, followed by *National Polytechnic Institute* and *Nanyang Technological University* (9), *University of Genoa* and *Nanyang Technological University* (4), as well as *University of Paris* and *National Research Council* (4).

The scientific collaborations between the top 24 authors are depicted in Fig. 5. Among the 24 authors, 7 are from Italy, 4 from Hong Kong, and 3 from Singapore. *Erik Cambria*, *Amir Hussain*, *Soujanya Poria*, *Alexander Gelbukh*, and *Raymond Yiu Keung Lau* were the most collaborative authors, collaborating with 8, 6, 5, 5, and 5 other authors, respectively. *Amir Hussain* and *Erik Cambria* were the closest collaborators, followed by *Soujanya Poria* and *Erik Cambria* (11), as well as *Alexander Gelbukh* and *Erik Cambria* (9). Moreover, the figure clearly shows several clusters formed by closely collaborative authors. For example, one cluster was mainly formed by *Erik Cambria*, *Amir Hussain*, *Soujanya Poria*, and *Alexander Gelbukh*. In addition, another cluster was formed by authors mainly from Hong Kong, including *Haoran Xie*, *Qing Li*, *Fu Lee Wang*, and *Raymond Yiu Keung Lau*, as well as *Yanghui Rao* from *Sun Yat-Sen University*. Two other clusters were formed by authors from the USA (i.e., *Rada Mihalcea* and *Louis-Philippe Morency*) and Italy (i.e., *Aldo Gangemi*, *Valentina Presutti*, and *Diego Reforgiato Recupero*).

We also calculated the betweenness and closeness centralities for each of the above-mentioned countries/regions, institutions, and authors (Table 8). The betweenness centrality is "a measure of others' dependence on a given node, and thus a measure of potential control." Closeness centrality is "a measure of access efficiency or independence from potential control by intermediaries (p. 1) [55]."

Fig. 4 Collaborative network of prolific institutions



The top three countries/regions ranked by betweenness were the UK, France, and Italy, and the top three ranked by closeness were France, Greece, and Austria. From the perspective of institutions, the top three ranked by betweenness were *Tsinghua University*, *National University of Singapore*, and *National Polytechnic Institute*. The top three ranked by closeness were *National Polytechnic Institute*, *Tsinghua University*, and *Nanyang Technological University*. From the perspective of authors, the top three ranked by betweenness and closeness were *Yunqing Xia*, *Raymond Yiu Keung Lau*, and *Amir Hussain*.

Key Term and Keyword Analyses

Table 9 lists the frequently used terms in the 308 sentic computing articles, with "sentiment (appearing in 195 articles, occupying 63.11%)" being the top one, followed by "social (114, 36.89%)," "language (108, 34.95%)," "learning (93, 30.10%)," "opinion (93, 30.10%)," "classification (92, 29.77%)," "feature (91, 29.45%)," and "network (87, 28.16%)." Comparing the proportions of each term in two continuous periods of time (i.e., 2011–2015 and 2016–2019), several terms showed an increase in usage, for example, "sentiment," "learning," "classification," "feature," "word," and "review." On the contrary, several terms experienced a decrease in usage, for example, "social," "language," "opinion," "emotion," and "knowledge."

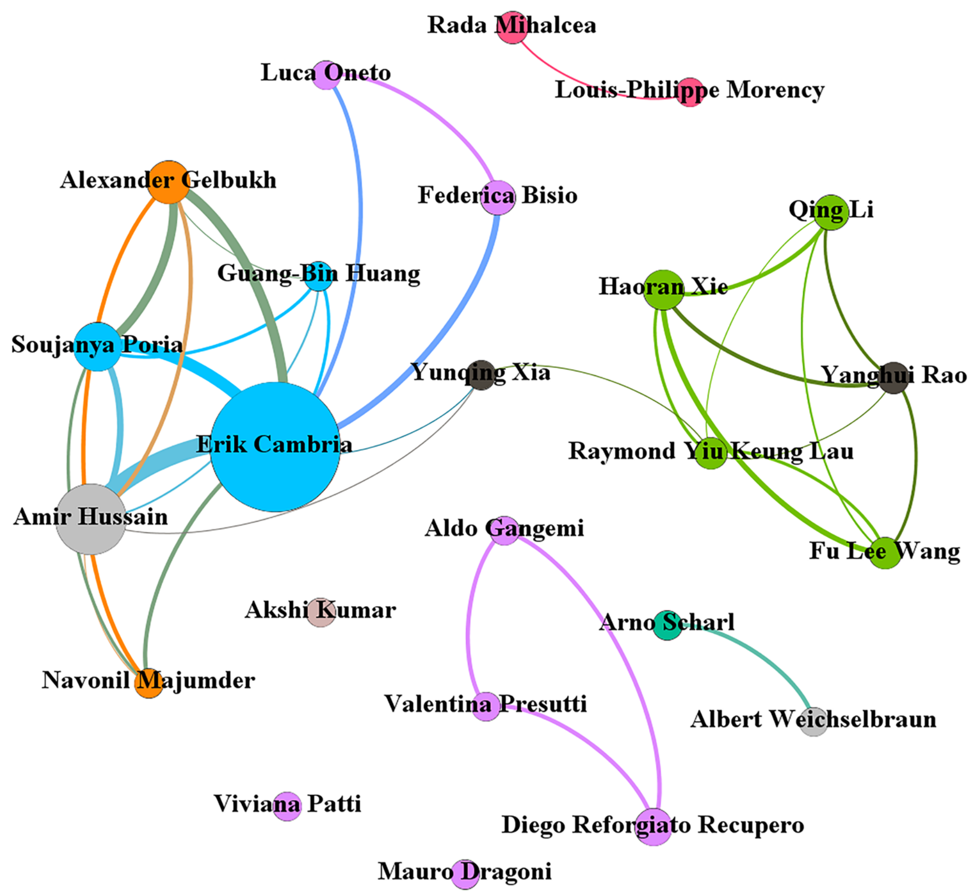
The most frequently used keywords in the 308 articles regarding sentic computing included "sentiment analysis," "NLP," "sentic computing," "opinion mining," "emotion recognition," and "Twitter." The evolution of keywords with a minimum frequency of three is visualized in Fig. 6. In the figure, the keywords are represented as nodes with size indicating their frequencies. The position of each keyword in the year axis was calculated by averaging the publication years of the articles in which the keyword appeared. The analysis of the figure indicates that some keywords appeared in an earlier stage, for example, "human emotion," whereas others appeared in a later stage, for example, "machine learning," "deep learning," and "attention model." We further visualized important keywords that have emerged in very recent years, for example, "student feedback," "signal processing," and "speech emotion recognition," as shown in Fig. 7. These keywords can be regarded as a reference for foreseeing the directions for future sentic computing research.

Major Topics and their Tendencies

Table 10 shows the results of the STM with seven topics, among which issues concerning *languages* (19.69%) were researched the most among authors, followed by *cyber issues and public opinion* (15.25%) and *deep neural networks and personality* (14.81%). The other four topics were *financial applications and user profiles* (13.44%), *affective and emotional computing* (13.33%), *opinion and review mining* (11.75%), and *sentic computing for the arts* (11.73%).

The tendency test results in Table 10 and the visualization of the annual proportion of each topic in Fig. 8 indicate that

Fig. 5 Collaborative network of prolific authors



several issues received increasing or decreasing interest in sentic computing research. Specifically, *financial applications and user profiles* showed an overall significant increase in research interest. However, there was a slight decrease during the recent few years. Furthermore, there were two other topics showing an increasing tendency in annual proportion, including *languages* and *deep neural networks and personality*. The other four topics exhibited a decreasing tendency in annual proportion at different degrees. Particularly, *cyber issues and public opinion* and *opinion and review mining* exhibited a dramatic decrease since 2011. However, in the recent few years, particularly since about 2015, a slight increase was observed. The topics *sentic computing for the arts* and *affective and emotional computing* have experienced a dramatic increase in research interest in previous years. However, since about 2015, they have attracted less attention from authors. Nevertheless, these four topics are still important in sentic computing research, particularly issues regarding concept-level sentiment analysis.

Topic Distributions of Major Contributors

The topic distributions of the top journals and contributors are visualized in Fig. 9. The analysis of Fig. 9a indicates that some journals, such as *IEEE Intelligent Systems* and *Knowledge-Based Systems*, showed a comparatively balanced interest in different issues. However, the majority of the listed journals showed an interest in particular topics. For example, *Cognitive Computation*, *Information Processing & Management*, and *IEEE Access* published more studies concerning *languages*, *sentic computing for the arts*, and *deep neural networks and personality*, respectively. In addition, *Natural Language Semantics* was particularly interested in *cyber issues and public opinion* and *sentic computing for the arts*.

In terms of topic distributions of countries/regions (see Fig. 9b), some countries/regions have a comparatively balanced interest in different topics, for example, Singapore, the USA, and the UK. However, others showed an interest in particular topics. For example, Hong Kong, France, and Spain published more studies concerning *financial applications and user profiles*, *sentic computing for the arts*, and *affective and emotional computing*, respectively.

From an institutional perspective (see Fig. 9c), *Nanyang Technological University* and *University of Stirling* showed a comparatively balanced interest in different issues, whereas the majority of the listed institutions showed an interest in particular topics. For example, *Massachusetts Institute of*

Table 8 Ten most central contributors based on betweenness and closeness centralities

	Betweenness		Closeness		Betweenness		Closeness		Betweenness		Closeness	
1	UK	136.84	France	0.00592	Tsinghua University	32.50	National Polytechnic Institute	0.00559	Yunqing Xia	47.5	Yunqing Xia	0.00526
2	France	129.75	Greece	0.00592	National University of Singapore	21.67	Tsinghua University	0.00556	Raymond Yiu Keung Lau	38	Raymond Yiu Keung Lau	0.00518
3	Italy	124.89	Austria	0.00588	National Polytechnic Institute	12.50	Nanyang Technological University	0.00553	Amir Hussain	30	Amir Hussain	0.00518
4	Austria	110.03	Germany	0.00585	Nanyang Technological University	12.33	National University of Singapore	0.00544	Erik Cambria	22	Erik Cambria	0.00513
5	USA	105.78	Ireland	0.00585	City University of Hong Kong	10.50	Chinese Academy of Sciences	0.00541	Guang-Bin Huang	13	Qing Li	0.00490
6	Pakistan	104.19	USA	0.00571	University of Stirling	10.17	Hong Kong Polytechnic University	0.00535	Navonil Majumder	8.5	Navonil Majumder	0.00488
7	Malaysia	87.76	Turkey	0.00571	Sun Yat-Sen University	8.00	City University of Hong Kong	0.00535	Qing Li	5	Yanghui Rao	0.00485
8	Germany	72.40	UK	0.00565	Hong Kong Polytechnic University	7.50	University of Stirling	0.00526			Guang-Bin Huang	0.00485
9	Canada	64.32	Netherlands	0.00553	Chinese Academy of Sciences	5.83	Sun Yat-Sen University	0.00518			Alexander Gelbukh	0.00444
10	India	59.29	Italy	0.00553	Carnegie Mellon University	2.00	Delhi Technological University	0.00513			Fu Lee Wang	0.00443

Table 9 Top frequently used terms in sentic computing studies

Terms	2011–2015		2016–2019		2011–2019	
	A	P	A	P	A	P
Sentiment	36	54.55%	159	65.43%	195	63.11%
Social	29	43.94%	85	34.98%	114	36.89%
Language	28	42.42%	80	32.92%	108	34.95%
Learning	14	21.21%	79	32.51%	93	30.10%
Opinion	23	34.85%	70	28.81%	93	30.10%
Classification	17	25.76%	75	30.86%	92	29.77%
Feature	15	22.73%	76	31.28%	91	29.45%
Network	19	28.79%	68	27.98%	87	28.16%
Word	11	16.67%	73	30.04%	84	27.18%
Emotion	22	33.33%	61	25.10%	83	26.86%
Medium	17	25.76%	61	25.10%	78	25.24%
Machine	14	21.21%	62	25.51%	76	24.60%
Knowledge	25	37.88%	48	19.75%	73	23.62%
Semantic	18	27.27%	55	22.63%	73	23.62%
Review	9	13.64%	63	25.93%	72	23.30%
Polarity	16	24.24%	54	22.22%	70	22.65%
Mining	15	22.73%	54	22.22%	69	22.33%
User	11	16.67%	54	22.22%	65	21.04%
Problem	11	16.67%	51	20.99%	62	20.06%
Detection	14	21.21%	41	16.87%	55	17.80%

A article count, *P* proportion

Technology and *Fondazione Bruno Kessler* published more studies concerning *cyber issues and public opinion* and *languages*, respectively. In addition, *City University of Hong Kong* and *Tsinghua University* are more interested in *financial applications and user profiles*.

In terms of topic distributions of authors (see Fig. 9d), *Erik Cambria*, *Soujanya Poria*, and *Amir Hussain* showed a comparatively balanced interest in different issues, whereas the majority showed an interest in particular topics. For example, *Diego Reforgiato Recupero* and *Federica Bisio* published more studies concerning *affective and emotional computing* and *deep neural networks and personality*, respectively. In addition, *Haoran Xie*, *Qing Li*, and *Fu Lee Wang*, as close collaborators in sentic computing research from Hong Kong institutions, showed a great interest *financial applications and user profiles*.

Scientific Collaborations in each Topic

We also explored the collaborations in each of the identified topics. In this way, we can address the question about "Did researchers tend to collaborative on certain topics?" Specifically, we explored the collaborations in the top 30 representative articles for each topic (Fig. 10). To enable a clear presentation, only collaborative partners with at least one collaboration are displayed in the figure. The results indicate that the topic *financial applications and user profiles* was the most collaborative from the perspectives of countries/regions, institutions, and authors.

Discussions

This study provides a topic-based bibliometric analysis of the sentic computing research articles published during the past decade, aiming to understand the progress, tendencies, and thematic structure of sentic computing. The results of our analyses indicate a flourishing development, as demonstrated by the constant increase of scientific literature. In this section, we present interpretations of the identified topics, implications for future research on sentic computing, and discussions on the limitations.

Interpretations of the Identified Topics

We identified seven major topics. The topic *languages* was the most discussed (13.69%), with discriminating terms such as "thai," "urdu," "word," "grammatical," and "persian," demonstrating the close relation of language and linguistic issues (e.g., dictionary, word, grammar, lexicon, and

Fig. 6 Evolution of keywords with a minimum frequency of three

semantics) to sentic computing. Representative articles for the topic were identified. For example, Peng and Cambria [56] presented an approach for constructing "a Chinese sentiment resource utilizing both English sentiment resources and the Chinese knowledge base (p. 90)," that is, the Nanyang Technological University Multilingual Corpus. Considering the sentiment lexicon information, Li et al. [57] proposed the lexicon-integrated two-channel "convolutional neural network (CNN)–long short-term memory (LSTM) and CNN–bidirectional LSTM (p. 1)" models.

In sequence, *cyber issues and public opinion* comprised a proportion of 15.25%, with discriminating terms such as "cyberbullying," "rumor," and "retweeting." This topic includes issues related to cyberbullying and rumor detection through public opinion mining. With the increasing prevalence of social media, cyberbullying is becoming increasingly harmful. Thus, automatic mechanisms to reduce the damage caused by cyberbullying are required in a timely manner. However, identifying cyberbullying is very challenging owing to "the heterogeneous form of the post (e.g., text, image, audio, and video), the improper writing style of online users, and the multilingual text (p. 4) [58]." In academia, there is a tendency for the understanding of the feasibility, possibility, and implication regarding the use of sentic computing to detect cyberbullying. One of the representative articles by Dinakar et al. [52] proposed a method to detect bullying by using advanced NLP techniques and a common sense knowledge base. In addition, the existence of continuously increasing volumes of rumors or fake news in social networks poses a significant threat to social stability, as such rumors have the potential to mislead public opinion, disrupt social order, and reduce government credibility [59, 60]. Therefore, rumor detection has gained considerable attention in recent years. A representative study by Akhtar et al. [61] proposed a method to detect rumor stances and predict veracities. In terms of rumor stance detection, they exploited the thread structure of a conversation using sentence embedding through a hierarchical LSTM network. In terms of veracity prediction, they defined and utilized diverse features for classifier learning with several machine learning algorithms.

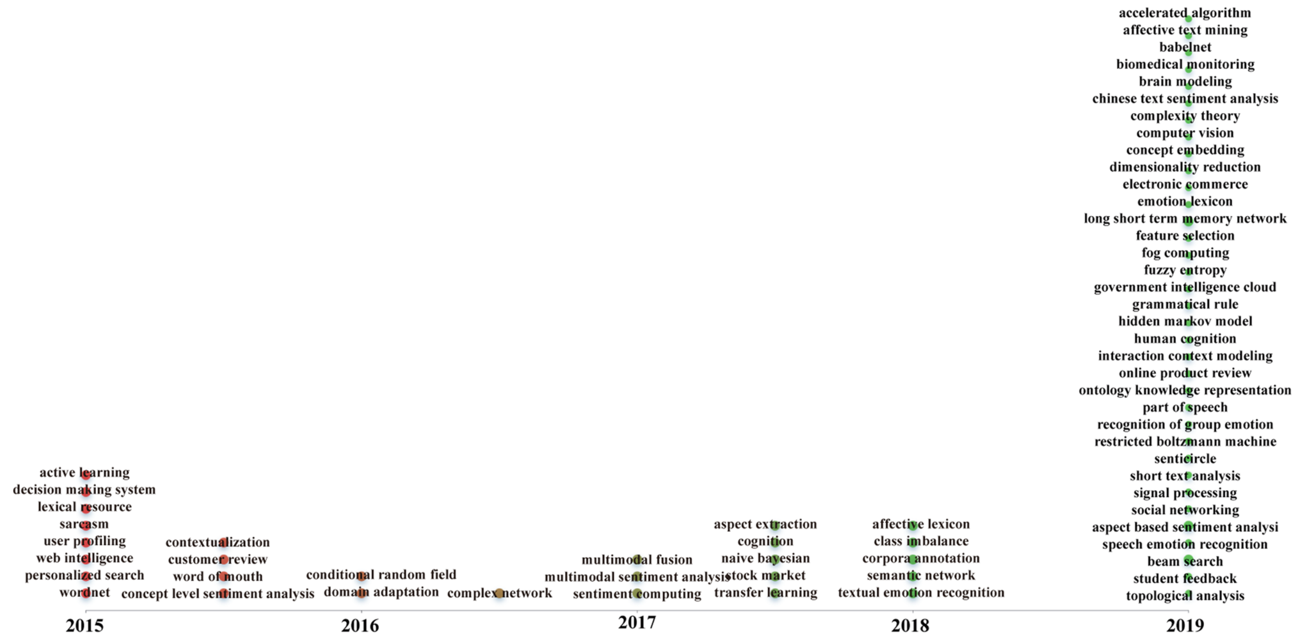


Fig. 7 Evolution of emerging keywords

The third topic was *deep neural networks and personality* (14.81%), with discriminating terms such as "deep," "neural," "learning," "network," "belief," "convolutional," and "supervision." Various models and algorithms [62, 63] based on deep neural networks are developed to resolve different issues, including personality detection. For instance, Majumder et al. [46] presented an approach driven by deep learning for personality prediction by detecting the existence of the Big Five traits in psychological profiles. Ahmad et al. [62] introduced a deep neural network model to efficiently predict the "dark triad (psychopath) personality traits of online users (p. 102)."

Fourth, *financial applications and user profiles* (13.44%) was an increasingly important area with discriminating terms including "stock," "financial," "synchronous," "discussion," "profile," "personalized," "market," and "price." Stock prediction is a promising task for investors. Particularly, a news-enhanced stock prediction based on social media sentiments has proven effective with high prediction accuracy [64, 65]. A representative study was conducted by Hájek [53], in which a bag-of-words (BoW) model and sentiment features of annual reports were combined abnormal stock return prediction. Specifically, both sentiment and BoW information

Table 10 Results of the STM model

Labels	Representative terms	%	*p*	Tendency
Languages	Thai, multi-domain, urdu, dictionary, word, grammatical, persian, embedding, lexicon	19.69	0.348	↑
Cyber issues and public opinion	Assertion, cyberbullying, rumor, deliberation, induced, photo, unacceptability, sense, retweeting	15.25	0.917	↑
Deep neural networks and personality	Deep, trait, neural, personality, supervision, learning, network, community, belief, convolutional	14.81	0.252	↑
Opinion and review mining	Trigger, adverb, review, product, helpfulness, customer, consumer, movie, online, rating	11.75	0.348	↑
Sentic computing for the arts	Sarcasm, figurative, color, expressive, inspired, nastiness, palette, sign, vague, artwork	11.73	0.348	↓
Financial applications and user profiles	Stock, profile, financial, market, price, personalized, folksonomy, tag, advertisement, tag-based	13.44	0.009	↑↑↑
Affective and emotional computing	Emotion, lexical, corpus, irony, senticnet, signal, affective, lexicon, detection, computing	13.33	0.917	↓

%: topic proportion; ↑(↓): topic with an annual increase (decrease) in proportion but not significant ($p > 0.05$); ↑↑(↓↓), ↑↑↑(↓↓↓), ↑↑↑↑(↓↓↓↓): topic with a significant annual increase (decrease) in proportion ($p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively)

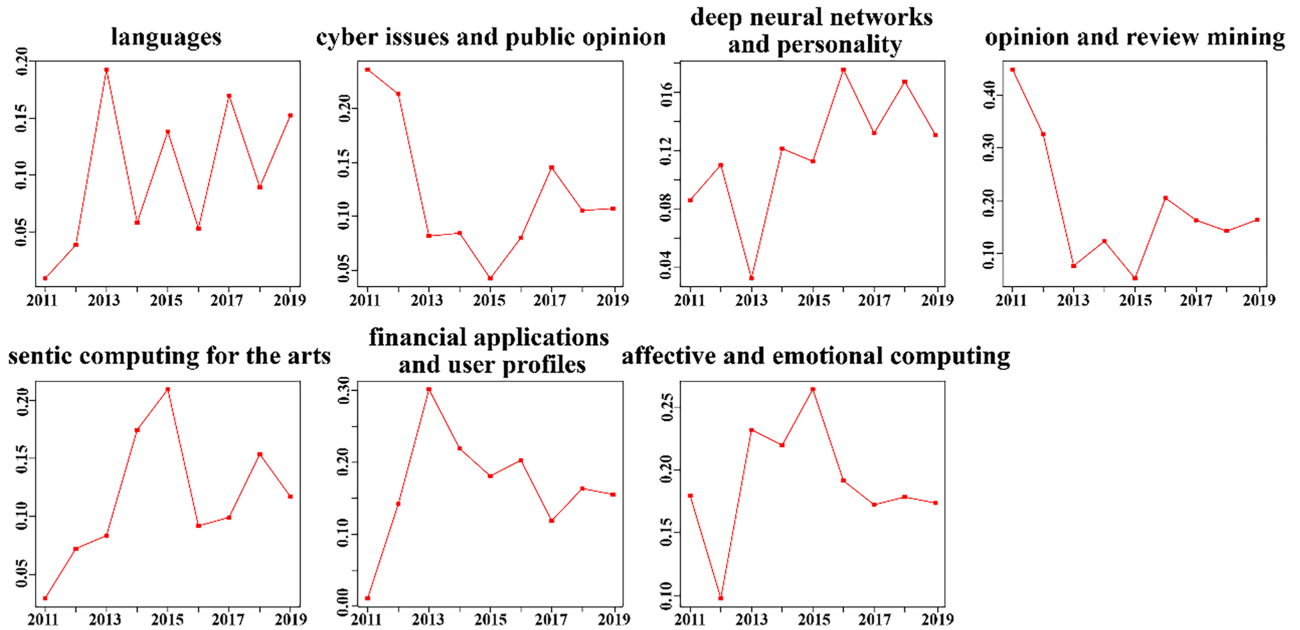


Fig. 8 Annual tendencies of the identified topics

from the annual reports were extracted to conduct "sentiment analysis based on two commonly used dictionaries, namely a general dictionary Diction 7.0 and a finance-specific dictionary (p. 343)." Moreover, personalized search is becoming increasingly essential and challenging due to the high demand for retrieval quality. Recently, a significant increase in user-generated data in collaborative tagging systems has been recognized as a result of the prevalence of web 2.0.

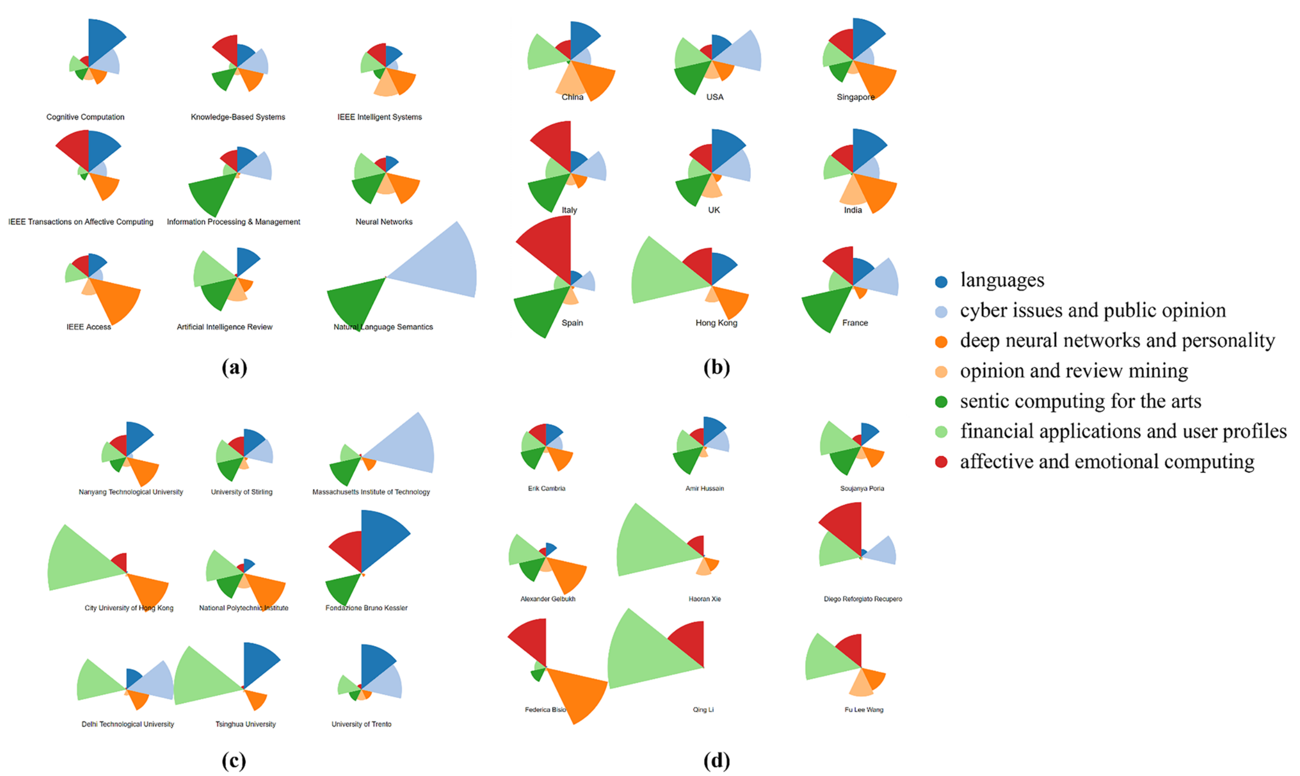


Fig. 9 Topical proportion distributions of the prolific **a** journals, **b** countries/regions, **c** institutions, and **d** authors

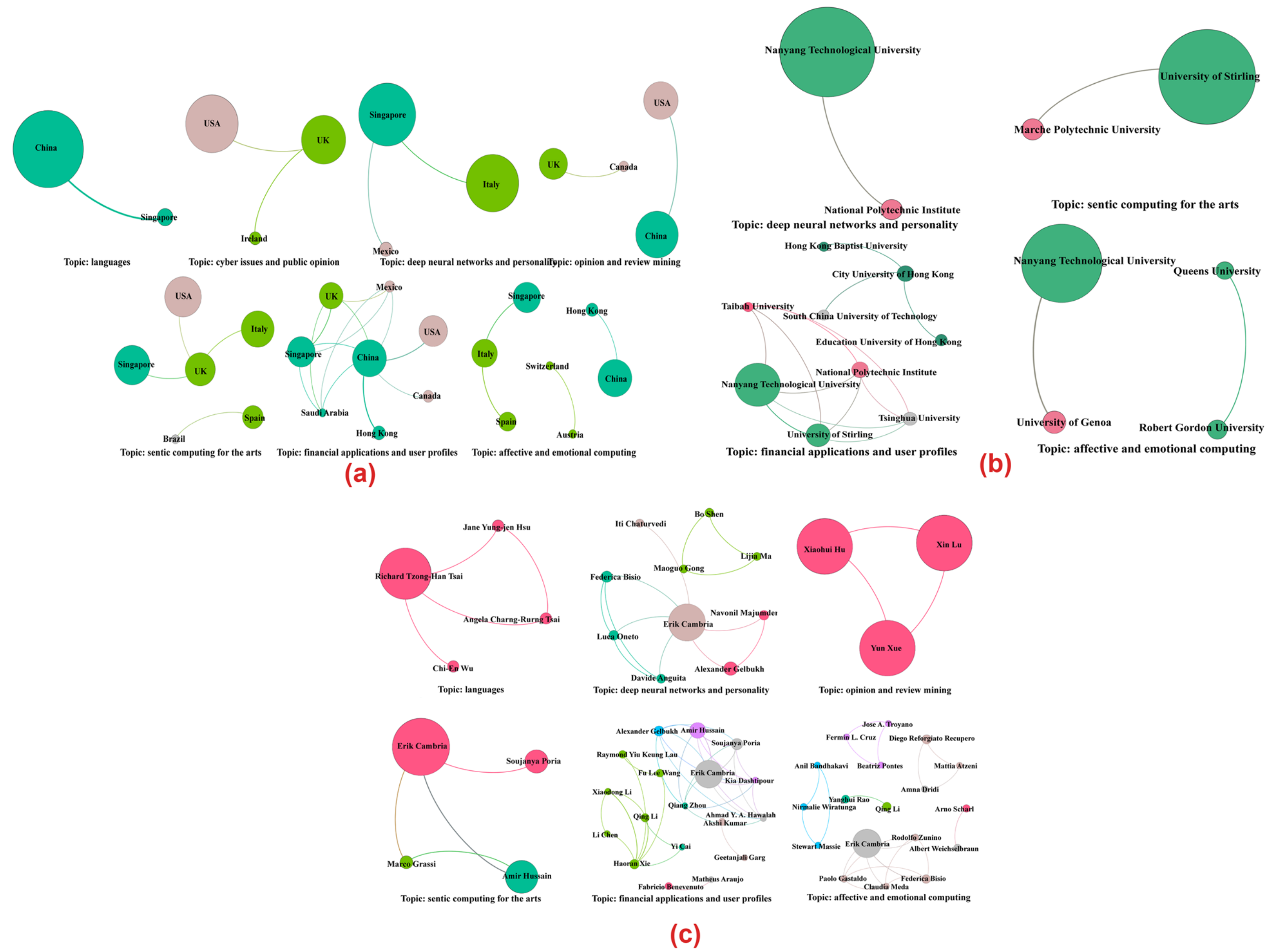


Fig. 10 Collaborations in each topic from the perspectives of **a** countries/regions, **b** institutions, and **c** authors

User profile construction is effective for various applications including personalized search systems [66–68]. Xie et al. [67] enriched user profiles with the basis of latent user communities in folksonomy data. There were several tasks, including tag-based user profile extraction, multi-faceted folksonomy graph construction, relationship normalization, and user similarity measurement, as well as user community identification and user profile enrichment.

Fifth, the topic *affective and emotional computing* accounted for 13.33%. The discriminating terms such as "emotion," "irony," "senticnet," "affective," and "detection" demonstrated the popularity of the application of sentic computing techniques for emotion classification and irony detection. Opinion and emotion extraction from texts has gained increasing attention from academia, particularly with the popularity of social media use, gathering large-scale datasets and lexical resources [69, 70]. In addition, the presence of irony in social media has brought a challenge to sentiment analysis [71]. Scholars have been working on irony detection with the use of sentic computing techniques. A representative study by Farías et al. [72] proposed an approach to explore how affective features were used based on diverse lexical resources in English. Their study proved that affective information was helpful for the identification of ironic and nonironic tweets.

Furthermore, *opinion and review mining* comprised a proportion of 11.75%, with discriminating terms such as "review," "product," "helpfulness," "customer," "consumer," "movie," "online," and "rating." Online reviews are helpful for potential users considering particular products or services and managers responsible for business decision making [73]. Sentic computing techniques have been increasingly adopted in social media marketing through customer review analysis [8]. Representative articles were identified. For example, Bi et al. [74] developed a framework for modeling customer satisfaction by "using LDA to extract customer satisfaction dimensions (CSDs) from online reviews," SVM to extract sentiment orientations, and ensemble neural networks "to measure the effects of customer sentiments toward different CSDs on customer satisfaction (p. 7068)."

In addition, the final topic was *sentic computing for the arts* (11.73%) with discriminating terms such as "figurative," "color," "expressive," "nastiness," "palette," "vague," and "artwork." Representative articles were identified. For example, Bertola and Patti [75] focused on the application of sentiment analysis to organize artworks in social semantic webs by developing emotional categories based on Plutchik's circumplex model.

Implications for Future Research on Sentic Computing

Based on our findings, we provide implications for future research on sentic computing, which are discussed in terms of algorithms/techniques, applications, tasks, strategies, and resources/tools.

From the perspective of algorithms/techniques, several issues are worth highlighting. Keywords such as "deep learning" and "attention model," as well as the topic *deep neural networks and personality*, are identified in the most recent literature, indicating a growing tendency of applying deep learning techniques in sentic computing research. Scholars are working on sentic computing models and algorithms based on deep learning techniques to address the issues concerning emotional and affective detection for emotion-sensitive applications. Deep learning techniques, for example, recurrent neural networks (RNNs), attention-driven algorithms, and CNNs, have been increasingly used in sentic computing research. CNNs [76, 77] can extract local and temporal semantic features from textual inputs. There are many sentic computing studies that adopt CNNs (e.g., [78–80]). For example, Mandhula et al. [80] aimed at predicting customers' opinions toward Amazon products with the use of selective memory architecture-enhanced CNNs. RNNs have been proven effective for resolving various (language) sequence learning issues [81] in several sentic computing studies (e.g., [82]). The attention mechanism [83] can further enhance deep model performance by assigning higher weights to discriminative words and has been proven effective in various NLP tasks, for example, neural machine translation, question answering, and machine comprehension. Various attention-enhanced RNNs have been proposed to enhance sentic computing and memory networks [84].

Sentic computing addresses issues concerning NLP through multi-disciplinary methods. Thus, in addition to NLP, many other disciplines are also involved, particularly those related to linguistic/language. Part-of-speech (POS) information can help to understand the structure of a sentence and is popularly used for sentiment analysis [85]. For example, the POS tags can be utilized to reduce the dimension of latent semantic analysis [86]. Researchers also use the POS combination approach for continuous phrase feature mining [87]. The grammar rule-based approach has also been widely adopted for sentiment analysis (e.g., [88]). In addition, semantic networks are increasingly adopted in sentic computing studies because of their ability to represent knowledge and support reasoning [89]. For example, WordNet, a large English lexical database, has been popularly used in sentic computing studies (e.g., [90, 91]).

In addition to techniques related to linguistics/language, techniques from many other disciplines are also popularly adopted. NLP has a close relation to many areas in cognitive science [92]. Cognitive language processing data (e.g., eye-tracking data) is effective for addressing complex classification issues like sentiment analysis [93]. The combination of signal processing techniques and artificial intelligence has also facilitated advances in intelligent systems used for detecting and processing affective information within multi-modal sources [44]. Techniques related to topological analysis, fuzzy entropy, and computer vision have also been increasingly applied in sentic computing studies (e.g., [6]).

There are also other types of techniques that should be mentioned. First, there is a tendency for the application of accelerated algorithms. For example, Pang et al. [94] proposed a fast supervised topic model to detect emotions in short texts. Second, there are studies (e.g., [95]) confirming the effectiveness of beam search algorithms to automatically construct domain-independent sentiment seed lexicons. Third, there are sentic computing studies (e.g., [96]) using the cloud, fog, and edge computing to maintain and process large-scale data over the Web, as well as studies (e.g., [47]) adopting restricted Boltzmann machines and autoencoders for representation learning.

From the perspective of applications, several areas are worth highlighting. For example, the analysis of online reviews to facilitate electronic commerce development has always been an important topic in sentic computing research. Such analyses can be divided into online product review mining and public opinion mining in social media. The growing interest in online product review analysis is indicated by the appearance of keywords such as "electronic commerce," "business," "internet," and "online product review." As e-business becomes increasingly popular, online product reviews that express buyers' sentiments are dramatically growing [97]. Understanding the sentiments of buyers toward a particular product is essential for increasing sales and driving business revenue [98]. Therefore, sentiment classification of online product reviews has become an important research topic. Hence, sentic computing researchers are highly recommended to continue working on effective approaches to detect emotional and affective issues contained within online product reviews.

The increasing research interest in public opinion mining in social media can be reflected by keywords such as "social networking" and the topics *cyber issues and public* *opinion* and *opinion and review mining*. This area comprises several emerging issues. First, research on the detection of cyberbullying has increased. The detection of cyberbullying behaviors is essential to take appropriate actions. Thus, intelligent techniques to automatically identify, detect, and assess cyberbullying from social multimedia data are required. Second, rumor detection is attracting increasing attention from a variety of organizations and government agencies to manage and maintain good decorum [61]. Third, the detection of retweeting behaviors has also received increasing attention from academia, as it is a primary mechanism of information diffusion on social media. Particularly, in recent years, sentic computing researchers have focused more on addressing users' subjective motivation to retweet. For example, Firdaus et al. [99] proposed a retweet prediction model that considered the mutual effects of topic and emotions/sentiment. Experiments showed that together with topics, users' emotions toward a particular topic were useful to model users' retweet decisions. In addition, research regarding the automatic prediction of personality traits has attracted increasing attention. Personality is "the combination of an individual's behavior, emotion, motivation, and characteristics of their thought patterns (p. 1) [11]." Researchers have proposed sentic computing techniques to automatically detect and predict personality from texts (e.g., [46, 100]).

Second, the application of sentic computing techniques in finance should also be discussed. Stock market volatility can be affected by "information release, dissemination, and public acceptance (p. 1) [65]." Such effects are becoming increasingly evident as social media data is rapidly increasing in terms of size and speed. Under such background, the news-enhanced stock prediction based on sentiments in social media is becoming increasingly prevalent [64], with an increasing number of available studies (e.g., [64, 101, 102]). For example, Dridi et al. [101] proposed a fine-grained supervised method for the identification of bullish and bearish sentiments in relation to corporations and stocks. The proposed method was trained using different feature sets that were composed of lexical and semantic features.

Third, there is a growing interest in applying sentic computing techniques in healthcare, which mainly involves emotion detection in health-related online discussions and user opinion mining for pharmacovigilance. Evidence has indicated the significant impact of online health-related discussions on participants' attitudes and behaviors. Furthermore, there are a number of empirical studies (e.g., [103, 104]) supporting the essential role of emotions in online discussions concerning health. In addition, pharmacovigilance with the applications of NLP algorithms has received increasing attention. Particularly, the increasingly available online health information shared by patients is valuable to facilitate the understanding of opinions about mental health and adverse drug reactions. Automatic emotion detection and opinion mining concerning healthcare can be benefited from the application of sentic computing techniques. Representative research studies are available. For example, Yadav et al. [78] proposed "a CNN-based model to identify different forms of medical sentiments that were inferred from users' medical conditions and treatments based on social media data (p. 2790)."

Fourth, there is a growing tendency to apply sentic computing techniques to facilitate government intelligence. Sentic computing can benefit governmental agencies in terms of identifying prevalent or controversial topics to take timely action to avoid common public dissatisfaction. Furthermore, there are various practical challenges concerning infrastructure development and implementation in conventional e-government [96]. However, the e-governance ecosystem has been re-defined with the advent of and advances in social media, mobiles, analytics, and cloud technologies. There are studies (e.g., [105]) showing that government can benefit from the application of sentic computing in terms of subjectivity and objectivity detection, thus opening new avenues to assist government agencies in making decisions concerning the management, planning, and logistics of public events.

Furthermore, there is a tendency for research on educational applications using sentic computing. Efficiently managing qualitative opinions of students to automatically generate reports is a challenging task. Researchers are attempting to use deep learning approaches for evaluating faculty teaching performance. For example, Sindhu et al. [106] proposed "a supervised aspect-based opinion mining system based on an LSTM model (p. 108729)" by predicting aspects expressed within students' feedbacks and specifying aspect orientations (i.e., positive, negative, and neutral) with high prediction accuracies.

In addition, research concerning the use of sentic computing techniques for arts is also encouraged. Casales-Garcia et al. [107] proposed an application of a cognitive-inspired qualitative color theory named QCharm, which was capable of constructing harmonic color palettes based on qualitative color description modeling. Specifically, with the use of Kobayashi's color space, cognitive/sentimental keywords indicating a feeling/lifestyle could be assigned to QCharm harmonic color palettes. QCharm was adopted to several food images to obtain feeling sets. Experiments indicated that the proposed method was useful for the creation of recommended systems for gastronomic marketing materials. It is also worth mentioning the Mood of the Planet [108], an interactive physical-digital sculpture that "has as its center-piece a large "arch" or "doorway" that emits colored light and sound as a form of visualization and sonification of the changing, live emotions expressed by people all around the Earth (p. 2)." Hourglass of Emotions [109] was used to pair emotions with color/texture combinations.

From the perspective of tasks, in addition to common tasks such as emotion extraction, affective text mining, and sentiment analysis, there are several issues worth noting. First, aspect-based sentiment analysis is challenging (e.g., word disambiguation in texts and domain-dependent polarity prediction [110]) to sentiment analysis. Scholars have been working on effective aspect-based sentiment analysis by proposing various methods. For example, Poria et al. [111] presented a sentic LDA for aspect-based sentiment analysis. By implementing common sense computing [3] to calculate word distributions in LDA [4], sentic LDA allowed the shift from syntax to semantics to improve clustering using the semantics associated with words. In addition, approaches developed based on deep learning algorithms are also available. For example, aiming at integrating explicit and implicit knowledge, Ma et al. [112] developed an extended LSTM named sentic LSTM for targeted aspect-based sentiment analysis. The extended LSTM could utilize explicit knowledge to control the information flows. Second, there is an increasing interest in group-level emotion recognition, which is difficult as "it is based on a single image (lack of temporal information), and the human faces are often in low-resolution (lack of facial details) (p. 1) [113]." Various algorithms have been proposed to resolve such issues [114, 115]. Third, speech emotion recognition is promising. Particularly, various methods are proposed to enhance the performance of speech emotion recognition by considering the impact of audio spectrograms on emotion detection. For example, Zhang et al. [79] developed a deep multiscale framework to detect spontaneous speech emotions by integrating a deep CNN model, a deep LSTM model, and a score-level fusion strategy. Fourth, concept-level sentiment analysis includes a semantic examination of concepts, mainly by adopting inference techniques to combine conceptual and affective information concerning natural language opinions [116]. Various approaches have been proposed to attain useful embeddings for the representation of textual information in common sense reasoning (e.g., [117]). In addition, interest in short text analysis with the use of sentic computing techniques is a focus of research. Particularly, in social networking sites, people are allowed to easily express their opinions through blogs and short text messages [118], generating unique content of massive dimensions. Thus, novel approaches for efficient and effective analysis of these data are necessary to further generate actionable knowledge to support decision making.

From the perspective of strategies, several issues have been addressed by sentic computing scholars. First, sentiment analysis of large-scale documents is of heavy complexity and requires a high cost [119]. Dimensionality reduction is commonly adopted to preprocess documents by enhancing the power of feature discrimination to ease such burden [120]. Second, sentiment analysis requires annotated corpora for learning and testing. In the era of big data, an automatic technique that can avoid, or at least significantly reduce, the workload of manual corpora annotation is needed. Scholars have been working on such issues. Canales et al. [121] exploited a bootstrapping approach based on intentional learning to achieve automatic annotation of large-scale emotion data. There were two major tasks. The first was to propose a similarity-driven categorization in which seed sentences were extended by distributional semantic similarity. The second was to train a supervised classifier. Furthermore, a contextualization strategy is usually adopted to increase classification accuracy in sentiment analysis by recognizing ambiguous terms, adding "context information for their disambiguation, and enriching the semantic knowledge bases for sentiment analysis (p. 3543) [122]." In addition, strategies to address class imbalance are highly encouraged. The serious label imbalance in multi-class tasks is a challenge for sentiment classification in many domains [123]. Various methods (e.g., heuristic re-sampling algorithm [73]) have been presented to alleviate the class imbalance.

From the perspective of resources/tools, several resources should be mentioned. First, SenticNet [10] uses techniques/knowledge in artificial intelligence, linguistics, and psychology to "infer the polarity associated with common sense concepts and encode this in a semantic-aware representation (p.1) [124]." Particularly, based on dimensionality reduction, SenticNet computes the affective valence of multi-word expressions and represents it in a format that can be accessed and processed by machines. Since the proposal of SenticNet, it has been popularly adopted to address issues concerning sentiment analysis and opinion mining (e.g., [125]) with different extensions being proposed. In particular, by integrating "logical reasoning within deep learning architectures, a new version of SenticNet (p. 105)," known as SenticNet 6 [126], was developed as a common sense knowledge base for sentiment analysis. Subsymbolic artificial intelligence was implemented to recognize meaningful patterns in natural language texts. The recognized patterns were then represented in SenticNet 6 with the use of symbolic logic. Deep learning was adopted for the generalization of words and multi-word expressions into primitives. Second, BabelSenticNet is an easy and replicable approach developed by Vilares et al. [127] to automatically generate SenticNet for various languages. It serves as a concept-level knowledge base for multilingual sentiment analysis. In addition, user profiles constructed from folksonomy systems have been proven useful for various applications ranging from personalized search to recommendation systems [68, 128].

Limitations and Reflections

We provide discussions on the limitations of this study. In terms of the analyzed data, there are several issues to be discussed. For instance, only journal articles were considered in our analysis, and conference papers were excluded. Hence, it is possible that some important studies were not included in our analysis. The justifications for the choice of journal articles are as follows.

First and foremost, we did not consider conference papers mainly due to the variations in publication quality. The quality of a journal article, particularly from journals of Science Citation Index (SCI) and Social Sciences Citation Index (SSCI), is usually ensured due to three aspects. First, Web of Science has established very rigorous criteria for selecting journals into their database (i.e., SCI/SSCI journals), which have been commonly acknowledged as a standard in the academic organizations [129, 130]. In contrast, there is no commonly recognized standard for conference proceedings. A journal article is subject to a very meticulous peer-review process, which is significantly more detailed than a conference review. This meticulous and iterative process helps improve both the research and paper quality. Second, it is extremely common that a limited number of accepted conference papers of high quality are selected to be published in journals. In addition, conference papers are usually short due to the page limit, while journal articles are longer with a better presentation of original contributions.

Second, our study aims to examine the general status and tendencies in sentic computing research. In literature, journal articles are popular and typical for examining research status and tendencies in a particular field, and their use sufficiently reflects tendencies and main topics. There have been a large number of review studies that only focused on journal articles (e.g., [23, 131–134]).

Furthermore, conference proceedings usually contain full and short papers. Short papers are usually early-stage, less-developed works in progress and are thus less representative in portraying the fields' development tendencies. Their identification in databases is not easy. Additionally, conferences usually vary considerably in the number of publications. Such an issue may cause the predominance of a few conferences in the results.

In conclusion, considering both the balance in publication quality and the publication representativeness, we opted for journal articles in this study. Nevertheless, future work oughts to explore how the intellectual structures of sentic computing vary across journal articles and conference papers.

Moreover, in this study, we only used "sentic*" as the search term, which may influence the results. However, the use of "sentic*" was considered acceptable after examining the data and results. Specifically, when we determined the query term, we initially identified "sentic*" as a highly important and exclusive term to sentic computing, as inspired by the work of Erik Cambria and Amir Hussain [135] in which "sentic*" is used in the majority of the content. Based on this term, we further extended the search list to include other relevant terms such as "sentiment analysis" and "opinion mining." Subsequently, we conducted searches using two sets of terms, one with only "sentic*" and the other with the extended list. We found that the use of the second set generated more than one hundred thousand records. In addition, our initial examination by randomly selecting five hundred records indicated that such a large dataset was problematic, as it contained considerable noise with low relevance. In contrast, examining the retrieval results using the term "sentic*," we found that most of the records were highly relevant, and the examination of the entire corpus indicated that such a dataset covered the major issues in the field. Thus, considering analysis efficiency, result reliability, and the costs of time and effort, we opted to use "sentic*" as our search term. The results of the data analysis validated the effectiveness of this choice, as major issues in sentic computing were detected. Nevertheless, in terms of future work, a strategy can be proposed to facilitate the screening of relevant studies within a very large dataset to allow more terms to be considered to generate more comprehensive results.

From a methodological perspective, limitations concerning the use of topic modeling and keyword analysis should be noted. As for keyword analysis, two issues may affect the results. First, there were many papers that did not provide keywords. Second, some publication sources may require authors to select keywords from their provided list. Hence, there are often cases in which provided terms are not the best "summarization of papers." Nevertheless, keyword analysis is still widely accepted as an effective method to help understand research foci in a particular period [38]. To overcome the limitations of keyword analysis and enable an in-depth exploration of research topics and tendencies, we also conducted analyses using a more advanced method such as STM. Hence, findings concerning the thematic structure and directions for future research were detected by joint interpretation of results of topic modeling and keywords analysis. The discussions in the previous sections indicate that our results reflect most of the major issues in the research field of sentic computing. However, a few issues remain to be uncovered. For example, issues concerning the application of sentic computing for human–computer interaction were not identified in our analysis. However, by examining our analyzed data corpus, such issues are mentioned. For example, Bell et al. [136] focused on social data analysis. Specifically, they first explored microblogging's potential in managing interactions between human beings and robots. They then presented and evaluated an architecture for extending social networks to connect humans and devices. Furthermore, the existence of overlapping topics and conceptually spurious words may lead to some issues not being detected. Conceptually spurious words are those that might be applied across multiple contexts and can cause problems under some circumstances. For example, in our data corpus, most of the studies related to sentic computing for human–computer interaction are highly related to *cyber issues and public opinion* and *deep neural networks and personality*. This is because the majority of research on sentic computing for human–computer interaction involved social media data mining or the use of deep learning techniques. Hence, many terms related to public opinion mining in social media are also frequently mentioned in topics concerning deep learning. Therefore, it is possible that issues concerning sentic computing for human–computer interaction have already been covered in the topics *cyber issues and public opinion* and *deep neural networks and personality*. In addition, it is possible that the adoption of synonyms and polysemy may lead to failures in identifying certain topics. Although topic modeling and keyword analysis may not provide as comprehensive results as manual techniques such as systematic review methodologies, they have significant advantages in automatically and rapidly managing a considerable amount of data, which is infeasible when using manual techniques. Additionally, the limited data involved in studies using manual techniques usually leads to the incompleteness of analysis results.

Despite the limitations, the findings in this study have generally achieved our research aim by providing a general understanding of the status, tendencies, and thematic structure of the sentic computing research. In terms of future work, it would be interesting to combine topic models and manual techniques to contribute to a more solid and comprehensive understanding of the field.

Conclusions

The scientific research of sentic computing has developed into a very important field during the past decade. This study is the first in-depth review regarding sentic computing, which was conducted by applying the STM and bibliometric analysis techniques.

This study presents the evolution of research topics concerning sentic computing over the last decade, with major journals and contributors being identified. Moreover, the interactions between co-authorship countries and institutions, as well as the author's community based on co-authorship connections, have been studied. In addition, seven research communities in the sentic computing field were identified with the use of STM, among which issues concerning *deep neural networks and personality*, *financial applications and user profiles*, *languages*, *sentic computing for the arts*, and *affective and emotional computing* are highlighted.

Therefore, as intended, this study comprehensively reviews the scientific growth and thematic structure of sentic computing for its further development. More importantly, the analytical framework with the combination of advanced STMs and statistical tests such as the Mann–Kendall trend test is demonstrated in this study to serve as an analytical tool in bibliometric studies.

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Declarations

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