Chen et al. Journal of Big Data (2025) 12:40
https://doi.org/10.1186/s40537-025-01068-y

Journal of Big Data

SURVEY

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A computational analysis of aspect-based sentiment analysis research through bibliometric mapping and topic modeling

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Abstract

With the rising volume of public and consumer engagement on social media platforms, the field of aspect-based sentiment analysis (ABSA) has garnered substantial attention. ABSA contains the systematic extraction of aspects, the analysis of associated sentiments, and the temporal evolution of these sentiments. Researchers have responded to the burgeoning interest by innovating new methodologies and strategies to address specific research challenges, thereby navigating complex scenarios and evolving challenges within ABSA. While existing reviews on ABSA encompass strategies, methods, and applications utilizing survey methodologies, a conspicuous gap exists in literature specifically addressing the development of methodologies and topics and their interaction in ABSA. Furthermore, the application of topic modeling and keyword co-occurrence has been limited in the extant literature. This study conducts a comprehensive overview of the ABSA field by leveraging bibliometrics, topic modeling, social network analysis, and keyword co-occurrence analysis to scrutinize 1325 ABSA research articles spanning the years 2009 to 2023. The analyses encompass research themes and topics, scientific collaborations, top publication sources, research areas, institutions, countries/regions, and publication and citation trends. Beyond examining and contrasting the connections between research topics and methodologies, this study identifies emerging trends and hotspots, providing researchers with insight into technical directions, limitations, and future research regarding ABSA topics and methodologies.

Keywords: Aspect-based sentiment analysis, Literature review, Computational analysis, Bibliometric mapping, Topic modeling, Social network visualization

Introduction

Aspect-based sentiment analysis

A distinct branch of sentiment analysis known as aspect-based sentiment analysis (ABSA) focuses on detecting and comprehending sentiments associated with specific features or components present in user-generated content [1, 2]. In the realm of Web 2.0, characterized by the abundant availability of user-generated information online, fine-grained sentiment analysis becomes imperative [3]. This analytical approach delves into various aspects of user experiences, emotions, and opinions, thereby providing valuable insights that can be instrumental in monitoring public sentiment and facilitating informed decision-making [4]. Among text-based analytics methodologies, ABSA stands out for its effectiveness in capturing perspectives, sentiments, judgments, and attitudes pertaining to a diverse array of subjects, including commodities, entities, events, and concerns [5].

Facilitating the interpretation of emotions within unstructured texts, discerning them as positive, negative, or neutral, and quantifying the intensity of these emotional expressions constitute ABSA's principal objective [6]. This specialized form of sentiment analysis has found utility across various industries, encompassing business, finance, politics, education, and services, as evidenced by its application in relevant studies [7–10]. Its widespread acceptance in commercial, governmental, and institutional domains, extending beyond academic realms, underscores its practicality and impact on decision-making stakeholders as a valuable decision-making tool for entrepreneurs, policymakers, and service providers alike [11].

Given that unstructured language constitutes the predominant form of user-generated content, ABSA faces challenges in consistently and reliably identifying sentiments [12]. Researchers have been actively engaged in devising strategies and tactics to increase sentiment analysis accuracy. The development of social media, fostering global communication, has further intensified the demand for sophisticated sentiment analysis [13, 14]. The dynamic nature of user-generated content and the evolving landscape of sentiment analysis are evident in the continuously diversified research topics, application domains, foundational methods, and technologies associated with ABSA, a phenomenon driven by continuous technological advancements.

Reviews of ABSA research

Systematic analysis of articles within specialized fields contributes to acquiring a comprehensive understanding of the subject matter [15, 16]. An inclusive summary of ABSA was presented by Truşcă and Frasincar [17], delineating a taxonomy for aspect extraction and highlighting techniques used in pivotal studies, including deep learning, machine learning, and pattern-based techniques. Bensoltane and Zaki [18] provided a thorough overview of Arabic ABSA research, outlining key challenges that various methods must address as well as research gaps. Meanwhile, Do et al. [19] provided a summary of deep learning for ABSA, illustrating the ABSA problem, the task's general framework from different perspectives, and issues pertinent to sentiment analysis and ABSA. Chauhan et al. [20] conducted a comprehensive examination of deep learning for ABSA. To enhance sentiment accuracy, Nazir et al. [21] pinpointed challenges associated with aspect and sentiment extraction, relational mapping across aspects, interactions, dependencies, contextual-semantic links, and sentiment evolution dynamicity prediction. Trisna and Jie [22] delved into deep learning techniques, exploring potential avenues for future research. Additionally, Liu et al. [23] introduced benchmark datasets, assessment measures, and deep learning methods for ABSA.

It is essential to acknowledge that significant issues surrounding ABSA have not been explored in existing reviews. For example, what are the main themes and research priorities in this field? In what ways have research trends shifted over time? Which countries, regions, and organizations have had the most impact on the field? How do these contributors cooperate? To address these questions, scholars should be willing to embrace innovative approaches, especially those derived from computer science.

Comparing with previous reviews

This study differentiates itself from previous reviews on ABSA in several ways:

Firstly, different from earlier reviews that primarily rely on narrative or systematic analysis methods, we adopt a bibliometric mapping approach combined with topic modeling that has been popularly adopted in the literature. For instance, Raman et al. [24] adopted thematic analysis and BERTopic modeling to analyze 397 publications on green and sustainable artificial intelligence research, while Li and Li [25] performed a bibliometric visual analysis using CiteSpace to analyze 921 papers on metaverse research in China. As the ABSA field evolves dynamically, driven by technological, sociological, and business factors, there is a growing need for continuous evaluations using bibliometric and data analytics techniques [26] to analyze large-scale literature data in an automatic manner to provide a macro-level understanding of ABSA research. By employing co-word analysis and topic modeling, this study maps the relationships between research themes, addressing a gap in prior reviews that tend to focus narrowly on specific techniques or methods [27].

Secondly, we introduce a nonparametric trend test to detect topics that are experiencing growing or waning interest within the ABSA field, along with a keyword evolution analysis. Previous reviews, such as those by Trisna and Jie [22], typically provide qualitative discussions of ABSA techniques without incorporating trend analyses. The inclusion of keyword evolution analysis and trend testing offers valuable, actionable insights to help researchers, particularly those new to the field, navigate emerging research directions, avoid redundancy, gain a deeper understanding of evolving trends, and assist researchers in aligning their work with future developments in ABSA.

Furthermore, beyond thematic analysis, we offer detailed insights into the social structure of ABSA research, including key contributors, influential publications, and collaborative networks. Such analyses are often lacking in the existing literature but are essential for new researchers to efficiently navigate the field, avoid redundant efforts, and identify potential collaborators.

In addition, while many existing reviews focus on predefined categories or a limited selection of papers, our study employs topic modeling-based bibliometric methods to analyze a large dataset to uncover themes and trends that may not fit traditional coding frameworks, thus offering a more comprehensive and nuanced overview of the ABSA research landscape.

Research objectives and questions

This study aims to systematically examine the state of knowledge advancements in the domain of ABSA through a bibliometric mapping and topic modeling approach, covering the period from 2009 to 2023. The main goal is to offer a thorough understanding of the emergence and development of ABSA as a research field. To achieve this, we outline three specific research objectives: (a) evaluating global contributions using bibliometric indicators such as H-index to evaluate the contributions of countries/regions and institutions to ABSA research; (b) analyzing scientific collaborations using social network analysis (SNA) to investigate collaborative relationships among institutions, countries, and regions to offer a macro-level view of cooperative networks within ABSA research; (c) identifying research hotspots and trends using keyword co-occurrence analysis, topic modeling, and non-parametric trend tests to uncover emerging research hotspots and trends to provide insights into evolving themes and suggest potential future research directions. Based on these objectives, we address four key research questions (RQs), which are derived from a range of bibliometric studies (e.g., [24, 25, 28]).

RQ1: What are the publication and citation trends, top publications sources, research areas, institutions, and countries/regions in ABSA research?
RQ2: What are the scientific collaborations in ABSA research?
RQ3: What are the major themes and topics in ABSA research?
RQ4: What directions should researchers pursue to advance ABSA research?

The primary contributions of this study can be summarized as follows:

Firstly, this study provides a macro-level, data-driven perspective on the current state and trends in ABSA research, identifying not only significant sources and contributors but also potential collaborators across scholarly and technological domains. Such a comprehensive bibliometric mapping approach is crucial for guiding researchers in navigating the evolving landscape of ABSA.

Secondly, this study offers an innovative method for understanding the structure and dynamics of ABSA-related research by pairing bibliometric methods with keyword co-occurrence analysis and topic modeling. These methodologies, as essential tools in the field of data analytics, are pivotal in revealing latent patterns, trends, and relationships within textual datasets, addressing the limitations of traditional narrative or qualitative reviews.

Thirdly, this study synthesizes author keywords, abstracts, and article titles to construct keyword co-occurrence networks to enable a nuanced analysis of ABSA methodologies and thematic evolution over time. Additionally, the study leverages community recognition, trend testing, and topic modeling to provide an enriched understanding of how key topics and methods have emerged and transformed within the field.

Lastly, in the context of the big data landscape, the present work significantly advances the analysis of ABSA research that focuses mainly on the analysis of large textual datasets by complementing existing qualitative reviews with an empirical foundation for understanding global contributions, collaboration patterns, and research trajectories. These insights are critical for equipping researchers, policymakers, and practitioners with actionable recommendations for steering technological advancements and shaping future research directions in ABSA.

Research methodologies

The present study adopted the principles and guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) Flow Diagram provided by Moher et al. [29] to systematically identify, select, and critically appraise scholarly articles relating to ABSA from the Web of Science (WoS). The choice of the PRISMA framework was intended to guarantee methodological rigor and minimize bias throughout the review process [24, 30]. The gathered data were subsequently analyzed by topic modeling, bibliometrics, SNA, and keyword co-occurrence analysis. To enhance comprehension, we present the overall research design of this study (Fig. 1), providing a visual representation of the suggested methodologies employed.

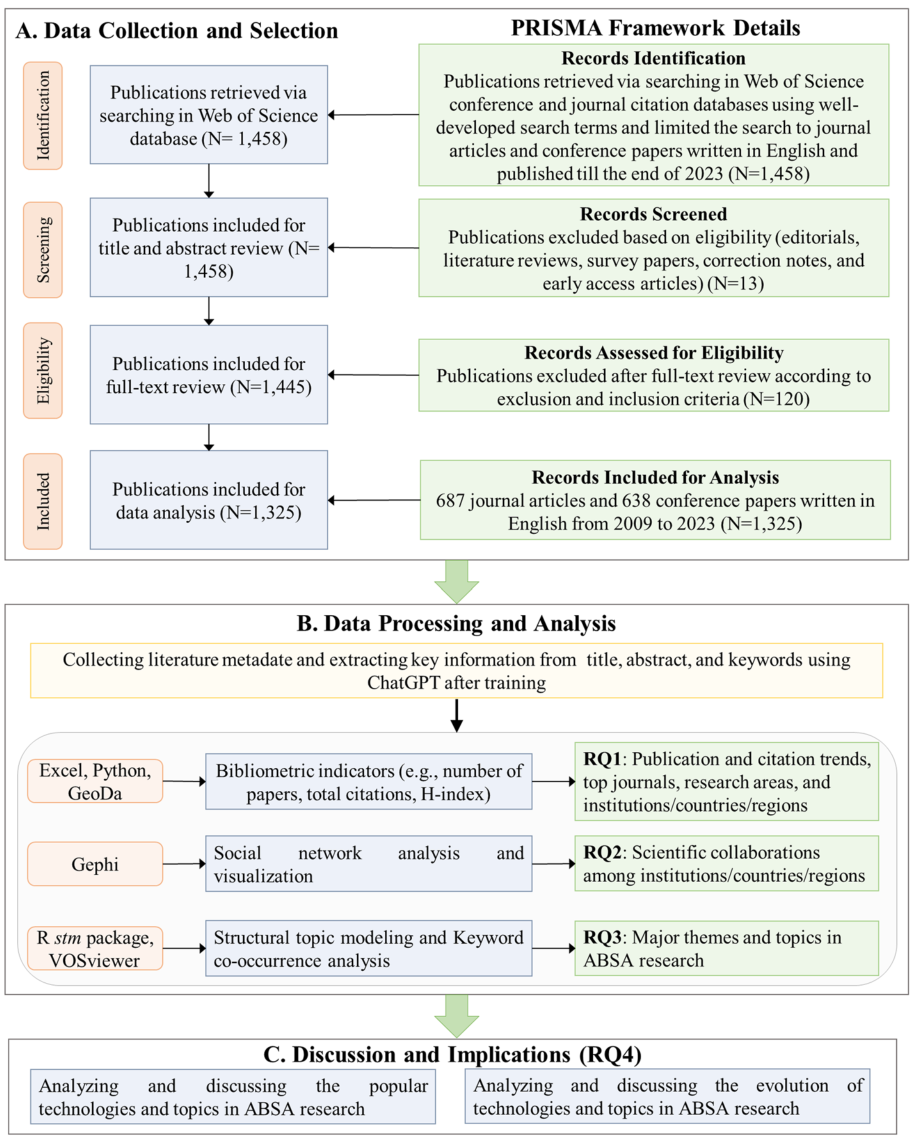

Fig. 1 Data search procedure following PRISMA and data analyses

Database selection and data retrieval

The data for the present research were obtained from the WoS platform. Four key citation databases were chosen for analysis: Conference Proceedings Citation Index—Social Sciences & Humanities (CPCI-SSH), Conference Proceedings Citation Index—Science (CPCI-S), Science Citation Index Expanded (SCI-Expanded), and Social Sciences Citation Index (SSCI). To facilitate article selection, an advanced search strategy utilizing Boolean expressions ("AND" and "OR") was implemented to enable the combination of keywords. The search query was applied to the TI = Title and TS = Topic fields. TI (Title) means that the search is restricted to words or phrases appearing specifically in the title of an article. TS (Topic Search) refers to a broader search that includes terms found in various sections of an article, including the title, abstract, author keywords, and Keywords Plus. Keywords Plus are terms generated by a proprietary algorithm in Clarivate databases, which are based on the titles of the references cited in an article, though these terms are not present in the article's title. The key distinction between the TI and TS fields is that the TS field is more expansive, as it searches not only the title but also the abstract and keyword fields, which allows for a more comprehensive capture of relevant articles. The specific retrieval strategy employed is outlined as follows:

((TS (Topic Search)=((("aspect-based" or "feature-level" or "aspect-level" or "aspect term" or "aspect categor*") AND ("sentiment analy*" or "opinion analy*" or "polarity analy*" or "affective analy*" or "subjectivity analy*" or "sentiment classifi*" or "opinion classifi*" or "subjectivity classifi*" or "polarity classifi*" or "affective classifi*" or "sentiment detect*" or "opinion detect*" or "polarity detect*" or "affective detect*" or "subjectivity detect*" or "sentiment identifi*" or "opinion identifi*" or "polarity identifi*" or "affective identifi*" or "subjectivity identifi*" or "sentiment categor*" or "opinion categor*" or "polarity categor*" or "affective categor*" or "subjectivity categor*" or "sentiment recogni*" or "opinion recogni*" or "polarity recogni*" or "affective recogni*" or "subjectivity recogni*" or "opinion target*" or "sentiment mining" or "opinion mining" or "semantic orientation" or "sentiwordnet*" or "sentic*" or "affective computing" or "sentiment learning" or "subjectivity learning" or "affective learning")))) NOT TS (Topic Search)=(("face image*" or "speech recognition" or "speech emotion" or "physiological signal*" or "music emotion*" or "facial feature extraction" or "video emotion" or "electroencephalography" or "biosignal*" or "image process*"))) NOT TI (Title)=(("facial" or "speech" or "sound*" or "face" or "dance" or "temperature" or "image*" or "spoken" or "electroencephalography" or "EEG" or "biosignal*" or "voice*"))*

In this study, conference papers hold equal significance to journal articles. The publications included in our analysis were limited to those published from January 2009 to the end of 2023 and encompassed publishing types such as "article" and "conference paper". A total of 1458 publications were gathered from the four previously mentioned databases.

Literature screening and data processing

The initially gathered set of 1458 publications underwent screening based on the specified criteria (see Table 1). These inclusion and exclusion criteria were determined

Table 1 Criteria for literature screening

Inclusion criteria	I-1	Aspect-based emotion polarity analytics and categorization
	I-2	Public sentiment regarding specific facets of issues, events, or products
	I-3	Aspect-based emotion scoring and evaluation
	I-4	Subtasks aimed at enhancing ABSA such as ATE and aspect category classification
	I-5	Development of techniques or algorithms for ABSA
Exclusion criteria	E-1	Identification and categorization of physical emotions and health conditions
	E-2	Identification of emotional body positions
	E-3	Studies centered on examining and recognizing emotions through different channels, including images, facial expressions, physiological responses, and electrical signals such as electrocardiograms
	E-4	Exploration of humans' capacity to identify emotions
	E-5	Examination of the concept of Theory of Mind
	E-6	Psychological or drug-based experimental research
	E-7	Development of ontologies, corpora, or datasets without conducting ABSA-specific experiments using models
	E-8	Editorials, literature reviews, survey papers, correction notes, or early-access articles
	E-9	Multimodal analysis, which incorporates data from multiple types of sources or modalities beyond text (e.g., images, videos, audio, or other sensory inputs), as opposed to relying solely on text analysis

by referring to previous reviews of sentiment analysis and its related topics (e.g., [28, 31, 32]) to maintain focus and consistency in the scope of the study while aligning with the objectives of our research. For example, regarding the exclusion criterion for studies that primarily focus on the creation of datasets for ABSA tasks, we excluded papers that merely introduce ontologies, corpora, or datasets without performing ABSA-specific experiments with models. For example, Omurca et al.[33] described the development of an annotated corpus for Turkish sentiment analysis at the sentence level and provided detailed linguistic analysis (e.g., aspect frequency, sentiment word usage, conjunctions, and negations). While Omurca et al. provided empirical results, these were statistical analyses of the corpus rather than results from ABSA-specific modeling experiments, thus it fell outside the scope of the present study. However, we included studies where the creation of datasets was paired with state-of-the-art ABSA-related model development or testing based on the created datasets, as these studies contribute directly to the advancement of ABSA methods. For instance, Giannakopoulos et al. [34] described a method for constructing a dataset for aspect term extraction (ATE) tasks by using attention mechanisms for selecting sentences likely to contain opinionated aspects and used the created dataset for training a model and performing ATE, an essential ABSA task, with distant supervision. As Giannakopoulos et al. combined dataset creation with ABSA-specific experiments and provided empirical evidence of model performance, contributing directly to methodological insights that could advance ABSA model performance, we thus considered it relevant to our analysis. In addition, the exclusion criterion for multimodal ABSA studies was inspired by Cui et al. [31], which focused on studies related primarily to the sentiment analysis of texts. Similarly, our study centered on ABSA in textual contexts. Thus, consistent with Cui et al., we excluded papers involving multimodal analysis where data from multiple types of sources or modalities beyond text (e.g., images, videos, audio, or other sensory inputs) were incorporated.

The initial screening of article titles and abstracts was conducted by the first and second authors to exclude editorials, literature reviews, survey papers, correction notes, and early access articles, achieving an inter-rater reliability of 98%. In cases of disagreement, the third author was consulted to assess whether the article should proceed to full-text screening, in accordance with the inclusion and exclusion criteria. As a result, 13 papers were excluded, leaving 1445 papers for a detailed eligibility assessment through full-text review. The full-text screening was also performed by the first and second authors to finalize the inclusion of 1325 papers, following the same procedure. The inter-rater agreement for this phase was 96%, and any discrepancies were resolved through consensus. The PRISMA flow diagram in Fig. 1 outlines each step of the search and selection process. For further data analysis, a final dataset comprising the 1325 publications, which includes 687 journal articles and 638 conference papers, encompassing the years 2009 to 2023, was established.

Keyword extraction

The objective of this process was to collect crucial information from the 1325 publications for the subsequent analysis of ABSA research methodologies and topics. Recognizing that each publication is constrained by a limited number of author keywords that may not comprehensively encapsulate the primary research ideas, we opted to merge the title and abstract to ensure a more comprehensive representation of the core concepts. This study adopted a prompt-based few-shot learning method, which leveraged ChatGPT's contextual understanding capabilities to infer patterns from provided input examples and perform the keyword extraction task without altering its underlying model parameters. More specifically, the keyword extraction process unfolded as follows. Firstly, the dataset was compiled by combining the title and abstract of each of the 1325 publications into a unified text. Secondly, 50 publications were randomly selected and annotated with labeled keywords, representing words or phrases representative of the main concepts in each publication. Thirdly, this study employed prompt engineering by providing ChatGPT with examples (the textual content and labeled keywords of the 50 publications) to guide it in inferring patterns and extracting keywords for the remaining 1275 publications. The prompt used in this study to direct ChatGPT's understanding and generation of relevant keywords was as: "*You are an expert in academic keyword extraction. Your goal is to identify key concepts and methodologies described in a publication. Given the title and abstract of an academic paper, generate a list of keywords that best represent the main topics, methods, and ideas. Use the labeled examples provided below to understand the task. Based on the examples, please extract the keywords for the following papers*". Furthermore, duplicates were eliminated by combining the retrieved keywords with the author keywords. Following this, synonyms were united, and the entire set of keywords was standardized. Finally, the keywords were checked, and phrases such as "aspect-based sentiment analysis" were eliminated.

Data analysis

We conducted analyses on the 1325 ABSA publications from 2009 to 2023 to address the RQs. The analyses encompass (1) patterns in publications and citation, top publication sources, research areas, institutions, and countries/regions; (2) scientific collaborations; (3) primary themes and topics; and (4) prospective directions, utilizing bibliometrics, SNA, keyword co-occurrence analysis, and topic models.

To answer RQ1, we employed a polynomial regression analysis to measure the annual count of publications and citations, with the top 10 publications being identified based on citation counts. Utilizing both Excel and Python, we conducted assessments on publication sources, research areas, institutions, and countries/regions using indicators such as total citation score, mean citation score, H index, number of publications in the top 10%, and proportion of publications in the top 10%. GeoDa was employed to visualize the spatial distribution of productivity [35].

To answer RQ2, we employed Gephi [36] in conjunction with SNA to generate a graphical representation of academic collaboration across institutions, nations, and regions. SNA utilizes graphical networks to outline structures resulting from interactions among entities, such as individuals, organizations, or countries, and quantifies these relationships. In this context, nodes represent entities, while lines depict measurable interactions. SNA proves to be an effective method for conveying quantitative insights into scientific cooperation among institutions or countries due to its visual clarity and accessibility, particularly for audiences lacking technical expertise.

Addressing RQ3, we employed topic modeling and keyword co-occurrence analysis methods to distinguish recurrent topics. A filtering threshold of 0.05 based on term frequency-inverse document frequencies was applied to improve word selection. Employing structural topic modeling (STM) based on an R stm package, we selected 13 topics from the ABSA dataset using coherence and exclusivity criteria [37].

The annual trends of these topics were examined using a non-parametric Mann–Kendall test [38]. Additionally, keyword co-occurrence analysis was integrated to attain a comprehensive understanding of the pivotal topics within ABSA research. To be specific, this study conducted a statistical analysis to assess the occurrence rate of the keywords, with the high-frequency keywords being extracted to form the basis for further analysis of the primary techniques and topics in ABSA. To identify keyword community networks, we computed keyword co-occurrences and employed VOSviewer for visualization [39].

To address RQ4, the visual and analytical outcomes were carefully examined, considering multiple factors such as research themes and research approaches dominant in each community. Furthermore, a thorough evaluation and discussion were conducted to clarify the progression of research methods and topics within the ABSA field.

Results and analysis

Publication and citation trends in ABSA research

Based on Table 2, there was an obvious increase in the number of publications over time, with a significant jump from 287 publications in the period 2014–2018 to 1014 publications in the subsequent period 2019–2023. The total citation score has experienced a substantial increase over the years, especially from 2014–2018 and 2019–2023.

Table 2 Production analysis

Indicators	2009–2013	2014–2018	2019–2023	2009–2023
Number of publications	24	287	1014	1325
Total citation score	8	1,062	17,240	18,310
Mean citation score	0.33	3.70	17.00	13.82
Total number of authors	72	937	4,005	5,014
Number of authors per publications	3.00	3.26	3.95	3.78
Total number of institutions	31	431	1845	2307
Mean institutions per publications	1.29	1.50	1.82	1.74
Total number of countries/regions	29	339	1301	1669
Mean countries/regions per publications	1.21	1.18	1.28	1.26

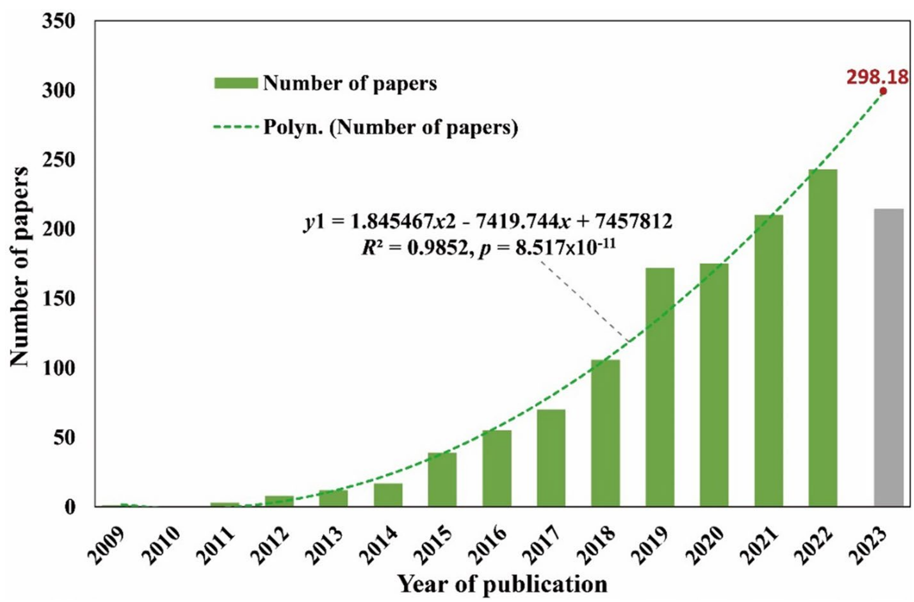

Fig. 2 Number of publications by year

This indicates a growing impact and recognition of the publications within the academic community. The mean citation score has fluctuated, with a peak in the period 2019–2023.

While there was a slight decrease from 2014 to 2018, the subsequent period saw a significant rise in the average citation score. The total number of authors has consistently increased, reflecting a collaborative trend in ABSA research. The number of authors per paper has slightly increased over the years, suggesting that, on average, more researchers are contributing to each paper. The total number of institutions, representing the institutions involved, has also seen a continuous rise. This indicates broader institutional collaboration in research. The indicator of the mean institutions per paper has increased, indicating that, on average, each paper is associated with more institutions. The total number of countries/regions involved has consistently increased, showcasing a globalized nature of research collaboration. The indicator of the mean countries/regions per paper has remained relatively stable, suggesting that, on average, each paper involves authors from a similar number of countries/regions. Overall, the results suggest a substantial growth in the volume of ABSA academic publications, increased collaboration among authors and institutions, and a rising impact measured by citation scores. The upward trends in the number of authors, institutions, and countries/regions indicate a more interconnected and collaborative landscape in ABSA research. The fluctuations in mean citation scores may be attributed to variations in the impact of individual ABSA publications.

Figure 2 illustrates the trend in the annual count of ABSA publications, providing a chronological overview from 2009 to 2023. Specifically, in 2009, there was one ABSA paper published. The year 2010 did not witness any ABSA being published. Starting from 2011, the number of publications steadily grew over time, with 3 publications in 2011, 8 in 2012, and 12 in 2013. A more significant growth is observed from 2014 onwards, with 17 publications in 2014 and a substantial increase in subsequent years. The number of ABSA publications continued to rise, reaching 39 in 2015, 55 in 2016, 70 in 2017, and 106 in 2018. The year 2019 saw a notable surge with 172 publications, and this upward trend continued in 2020 with 175 publications. The peak in ABSA publications occurred in 2022, with a total of 243 papers, followed by a slight decrease to 214 publications in 2023. Overall, the results indicate a growing interest and research activity in ABSA, with a substantial growth in the number of published publications, particularly in the later years of the timeline. This suggests a heightened focus on exploring and advancing methodologies related to analyzing sentiment with respect to different aspects within the field.

Figure 3 presents the trend of annual citations for ABSA research, providing a chronological overview from 2009 to 2023. In the early years from 2009 to 2011, there were no recorded citations for ABSA publications, indicating a minimal impact or visibility in the academic community during this period. In 2012, there was a modest start with 2 citations,

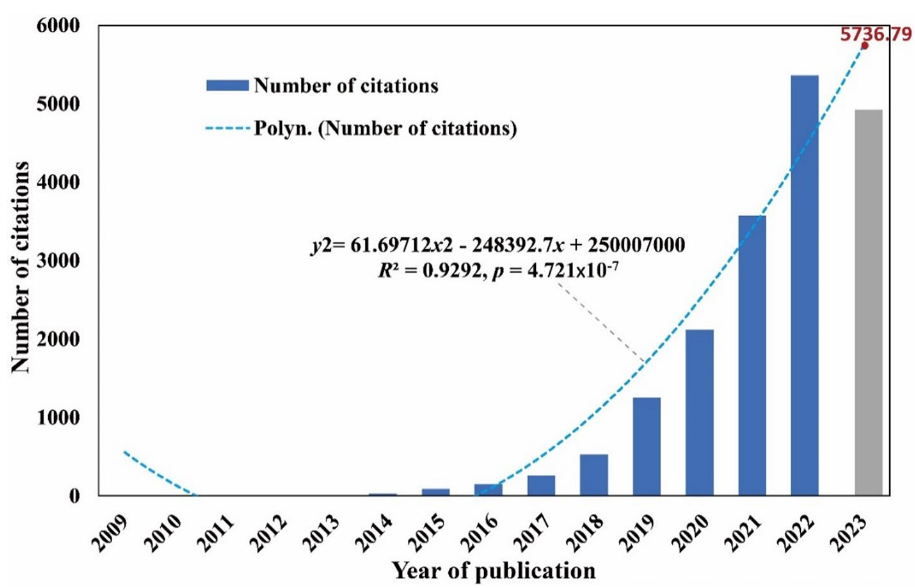

Fig. 3 Number of citations by year

suggesting an initial recognition and interest in ABSA research. The number of citations increased gradually in the subsequent years, with 6 in 2013, 30 in 2014, and a notable rise to 90 in 2015. The trend continued with a steady increase in citations, reaching 152 in 2016 and 260 in 2017, indicating a growing impact and acknowledgment of the research. The year 2018 marked a substantial increase with 530 citations, reflecting a heightened interest and influence of ABSA publications in the academic community. The impact continued to grow significantly in 2019, where the publications received 1255 citations, emphasizing the increasing importance and relevance of the research. In 2020 and 2021, the number of citations experienced a remarkable surge, reaching 2123 and 3577, respectively. This suggests a peak in the impact of ABSA publications during these years. The greatest number of citations occurred in 2022, totaling a notable 5362 citations, signifying widespread recognition and influence in the academic domain. In 2023, while still substantial at 4923 citations, there was a slight decrease compared to the previous year, indicating potential variations in the impact of ABSA publications. Overall, the results depict a positive and upward trend in the citations received by ABSA publications, showcasing a growing impact within the academic community.

Table 3 shows the top 10 highly cited ABSA publications, detailing information such as the number of citations and the publication year for each influential paper. Examining the publication years of these top-cited articles, the range spanned from 2014 to 2020. This temporal diversity suggests that the earlier publications may hold foundational status in specific topics, demonstrating enduring relevance over time. Notably, the highest-cited paper boasted more than twice the number of citations compared to the six-ranked paper. The second paper surpassed the tenth-ranked paper by more than 185 citations. Beyond the top two publications, the distance in citation counts narrowed among the remaining seven articles. This pattern implies a closer competition in terms of citations received, indicating that these publications are relatively more closely ranked in terms of their influence within the field of ABSA.

Top publication sources and research areas

Table 4 showcases the top 13 sources with the highest publication count related to ABSA throughout the study period. IEEE Access stood out as the top source with the largest

Table 3 Top 10 publications ranked by total citation score

Paper titles	TCS	Y
"Interactive attention networks for aspect-level sentiment classification"	497	2017
"Explicit factor models for explainable recommendation based on phrase-level sentiment analysis"	396	2014
"Targeted aspect-based sentiment analysis via embedding commonsense knowledge into an attentive LSTM"	331	2018
"Aspect based sentiment analysis with gated convolutional networks"	302	2018
"BERT post-training for review reading comprehension and aspect-based sentiment analysis"	288	2019
"Utilizing BERT for aspect-based sentiment analysis via constructing auxiliary sentence"	250	2019
"Multi-grained attention network for aspect-level sentiment classification"	240	2018
"An unsupervised neural attention model for aspect extraction"	221	2017
"Relational graph attention network for aspect-based sentiment analysis"	213	2020
"Aspect-based sentiment classification with aspect-specific graph convolutional networks"	209	2019

Note: Y: TCS: Total citation score; Year of publication

Table 4 Most relevant publication sources

Publication sources	P	PP	TCS	MCS	H	P (top10%)	PP (top10%)
IEEE Access	66	4.98%	953	14.44	16	6	9.09%
Knowledge-Based Systems	57	4.30%	1435	25.18	21	14	24.56%
Neurocomputing	34	2.57%	540	15.88	14	4	11.76%
International Joint Conference on Neural Networks	28	2.11%	162	5.79	4	1	3.57%
Applied Intelligence	25	1.89%	283	11.32	9	2	8.00%
Applied Sciences-Basel	22	1.66%	161	7.32	6	1	4.55%
Conference on Empirical Methods in Natural Language Processing	22	1.66%	773	35.14	13	6	27.27%
AAAI Conference on Artificial Intelligence	20	1.51%	950	47.50	14	9	45.00%
The Association for Computational Linguistics	20	1.51%	1,626	81.30	16	13	65.00%
Expert Systems with Applications	18	1.36%	590	32.78	12	6	33.33%
Information Processing & Management	18	1.36%	502	27.89	11	5	27.78%
Journal of Intelligent & Fuzzy Systems	17	1.28%	125	7.35	4	1	5.88%
Journal of Supercomputing	16	1.21%	49	3.06	5	0	0

Note: P: Number of publications; PP: Percentage of total publications; TCS: Total citation score; MCS: Mean citation score; H: H-index; P (top10%): Number of publications in top 10% Rank; PP (top10%): Proportion of publications in top 10%

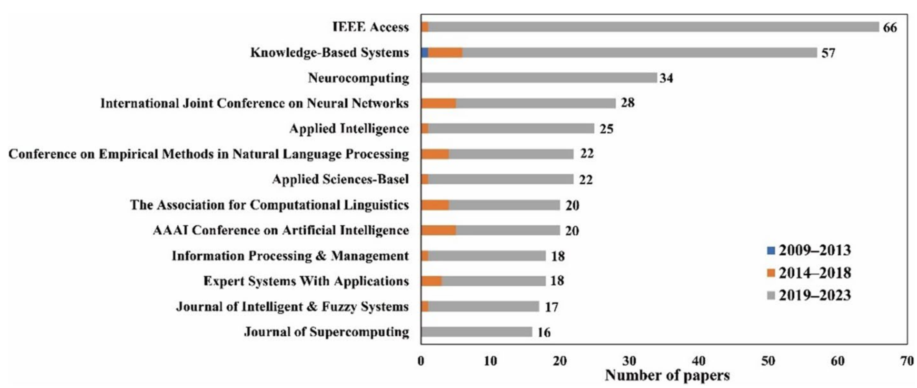

Fig. 4 Number of papers of the top publication sources

number of total articles, nearly doubling the count of the third-ranked source. However, when analyzing the total citation score across the top 13 sources, IEEE Access, initially in the lead, dropped to the third position. Significantly, the Association for Computational Linguistics displayed a distinct impact within the field with a top PP (Top 10%) value of 0.65. In terms of H-index, Knowledge-Based Systems secured the first position, followed by The Association for Computational Linguistics.

The top 13 sources are shown in Fig. 4 according to the number of ABSA-related publications that were published during three periods. IEEE ACCESS is placed first, with almost twice as many points as the third-place source. Most of the publications were published during 2019 and 2023, demonstrating this field's explosive development in recent years. Of the 13 sources, 12 did not release ABSA publications over the first four years, 2009–2013, suggesting that an increase in a variety of scientific endeavors has resulted from the diversification of new areas within ABSA research.

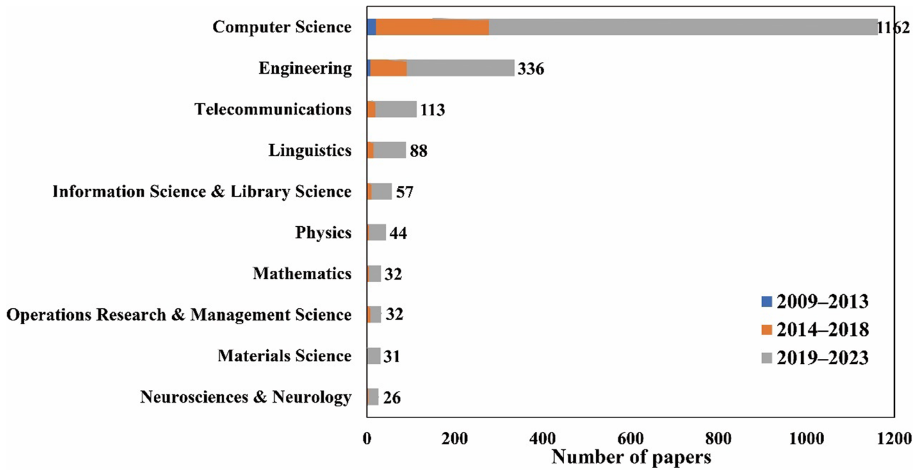

Fig. 5 Most relevant application domains and research areas

The distribution of ABSA across application domains and research areas, together with the corresponding number of publications are shown in Fig. 5. Computer Science accounted for 87.70% of the published publications, and ABSA models were also widely used in domains including physics, engineering, telecommunications, information science, and library science.

Top institutions and countries/regions

Table 5 showcases the leading 10 institutions with the most ABSA publications during the study period. The Chinese Academy of Sciences emerged as the top institution, surpassing the tenth-ranked institution by almost doubling the total number of publications. When measured by the indicator of total citation score, Nanyang Technological University ranked first among the 10 institutions listed in Table 5. According to the Proportion of Publications (PP top 10%) indicator, Tsinghua University, with a PP value of 0.35, secured the top position. In terms of the H-index, Nanyang Technological University held the top rank, with the Chinese Academy of Sciences in second place. This suggests the ABSA publications contributed by authors affiliated with Nanyang Technological University were associated with a greater impact and influence within the ABSA research community.

According to Fig. 6 which shows the top 10 institutions with the greatest publication count in ABSA articles during the investigated years, eight Chinese universities were prominent. Tsinghua University published ABSA publications throughout the three periods. In the second four-year period (2014–2018), Nanyang Technological University outperformed the Chinese Academy of Sciences by publishing a much greater number of articles than the former. The most published articles among the 10 universities occurred in the last four years (2019–2023), exceedingly at least 82% of all publications.

Table 6 showcases the leading 10 countries/regions with the highest number of ABSA publications over the study period. Among these countries/regions, China stood out with the highest number of articles, nearly four times the count of the second-ranked country. With a top PP indicator (Top 10%) value of 0.283, Singapore has demonstrated

Table 5 Productive institutions

Institutions	P	PP (%)	SIP	MIP	PMIP (%)	TCS	MCS	H	P (top10%)	PP (top10%)
Chinese Academy of Sciences	37	2.79	2	35	94.59	372	10.05	12	2	5.41%
Nanyang Technological University	31	2.34	8	23	74.19	1420	45.81	16	9	29.03%
Erasmus University	27	2.04	19	8	29.63	309	11.44	10	3	11.11%
South China Normal University	27	2.04	15	12	44.44	237	8.78	6	2	7.41%
Beijing University of Posts and Telecommunications	26	1.96	9	17	65.38	220	8.46	9	2	7.69%
Wuhan University	26	1.96	13	13	50.00	375	14.42	6	3	11.54%
Harbin Institute of Technology	24	1.81	4	20	83.33	553	23.04	9	6	25.00%
University of Chinese Academy of Sciences	24	1.81	1	23	95.83	223	9.29	9	2	8.33%
Tsinghua University	20	1.51	3	17	85.00	1,008	50.40	10	7	35.00%
Shandong Normal University	18	1.36	4	14	77.78	135	7.50	8	0	0.00%

The same as Table 4 except for three indicators (SIP: Single institution publications; MIP: Multiple institutions publications; PMIP: Percentage of multiple institutions publications)

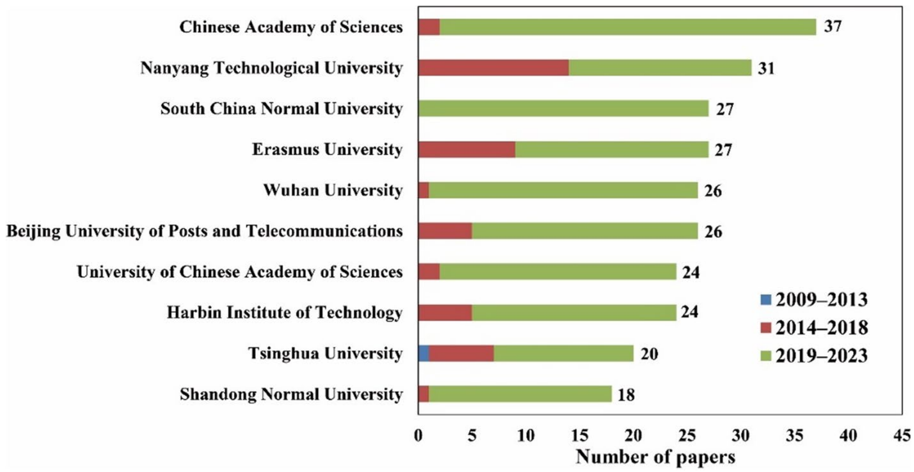

Fig. 6 Number of papers of the top institutions

Table 6 Productive countries/regions

C/R	P	PP (%)	SCP	MCP	PMCP (%)	TCS	MCS	H	P (top10%)	PP (top10%)
China	643	48.53	494	149	23.17	9,706	15.09	47	68	10.58%
India	160	12.08	138	22	13.75	1531	9.57	23	11	6.88%
USA	106	8.00	36	70	66.04	3,123	29.46	26	24	22.64%
Singapore	53	4.00	17	36	67.92	2,234	42.15	21	15	28.30%
Pakistan	43	3.25	14	29	67.44	407	9.47	12	1	2.33%
UK	37	2.79	9	28	75.68	847	22.89	14	6	16.22%
Netherlands	34	2.57	25	9	26.47	324	9.53	10	3	8.82%
Spain	34	2.57	24	10	29.41	507	14.91	12	4	11.76%
Australia	32	2.42	4	28	87.50	233	7.28	6	2	6.25%
South Korea	32	2.42	17	15	46.88	369	11.53	10	3	9.38%

The same as Table 4 except for three indicators (C/R: Countries/regions; SCP: Single country/region publications; MCP: Multiple countries/regions publications; PMCP: Percentage of multiple countries/regions publications)

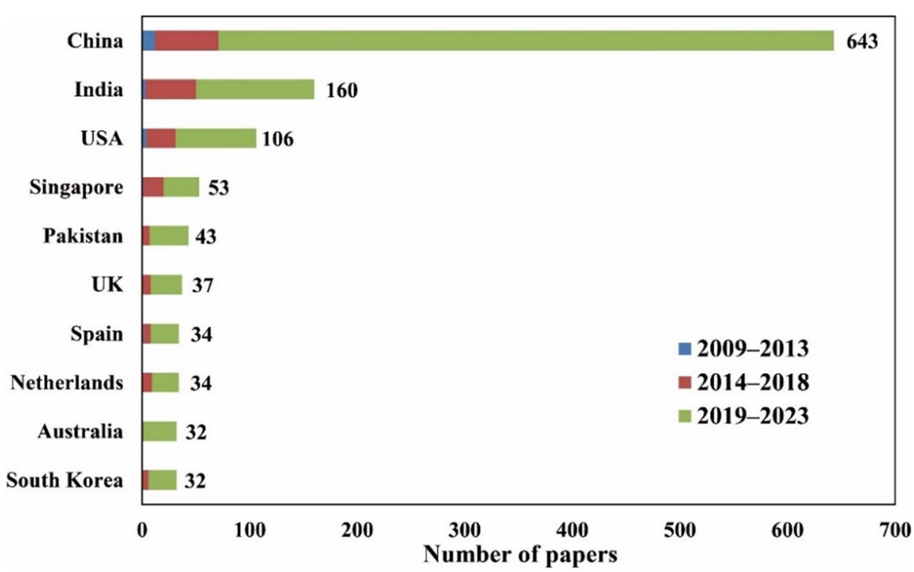

Fig. 7 Number of papers of the top countries/regions

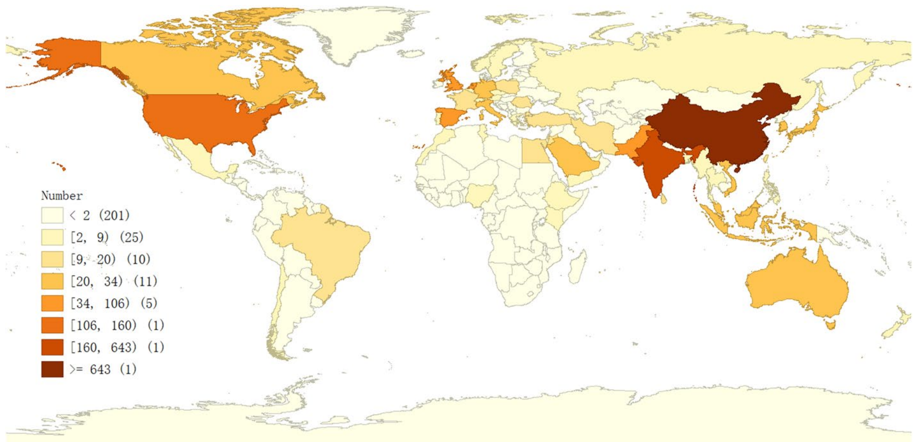

Fig. 8 Geographic distribution

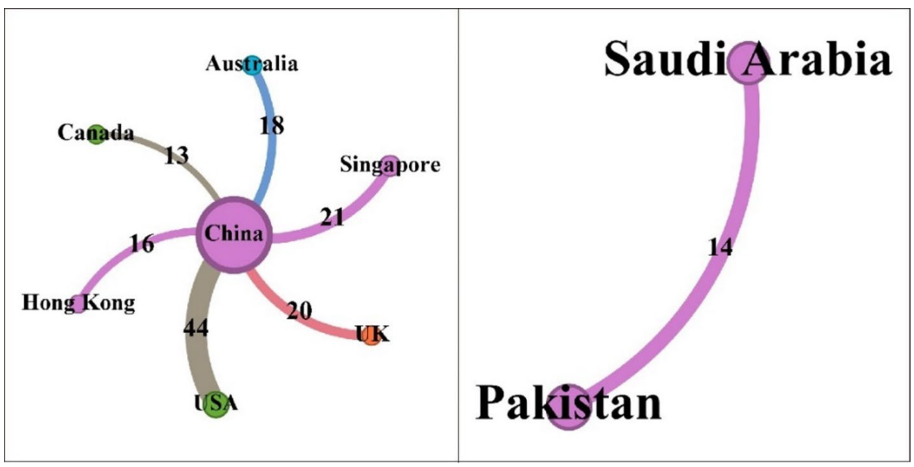

Fig. 9 Collaborations among countries/regions with 13 < = frequency < = 44

its distinct impact within the field. Looking at the H-index, China was in the first position, followed by the USA, suggesting that the ABSA publications contributed by authors affiliated with Chinese institutions were generally associated with a greater impact and influence within the ABSA research community.

The number of papers of the top 10 productive countries/regions in three periods is shown in Fig. 7. During the previous four years, the top 10 showed a notable growth in the number of papers. China produced around 3.5 times as many publications as India did during this period, accounting for almost 89% of its entire output, while the nine followers consistently demonstrated year-over-year growth.

Figure 8 displays the geographic distribution of published papers, with varying shades of color indicating the volume of publications and darker hues representing a higher number of documents. The map shows that China and India were the leading contributors to ABSA research in Asia. In North America, the USA has published the maximum number of articles on ABSA. Notably, South America stood out as the continent with the fewest countries contributing to the publication of ABSA articles during this period.

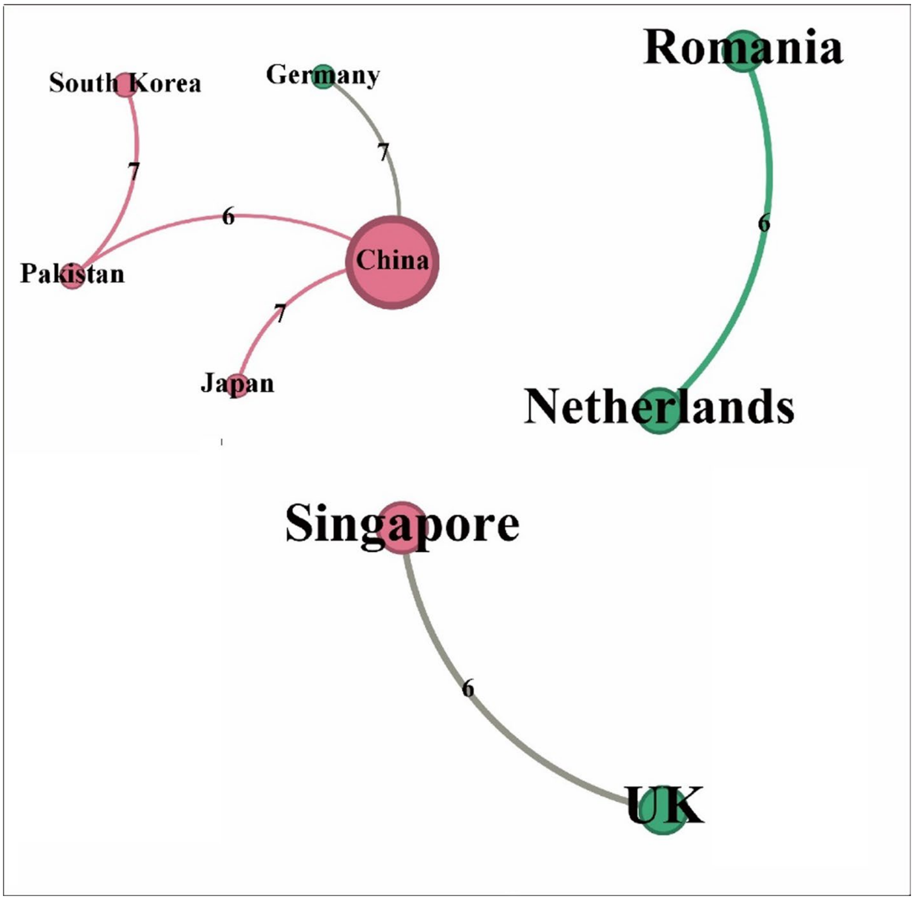

Fig. 10 Collaborations among countries/regions with 6 < = frequency < = 7

Collaboration analysis

Figure 9 depicts the collaborations between 9 countries/regions, with the frequency of partnerships ranging from 13 to 44. Of these, 5 are located in Asia (represented by pink nodes). Significantly, the USA and China showed the most substantial collaboration, being involved in 44 articles, followed by China and Singapore (21), China and the UK (20), and China and Australia (18). Figure 10 highlights partnerships between 9 countries/regions, with collaboration frequencies varying between 6 and 7. Among these, 5 are from Asia (depicted as red nodes) and 4 are from Europe (shown as green nodes). There are three distinct collaborative clusters: (1) Germany, South Korea, Pakistan, Japan, and China; (2) Netherlands and Romania; and (3) Singapore and the UK. Figure 11 illustrates the collaborations among 12 countries/regions, with partnership frequencies between 4 and 5. Of these, 9 countries/regions are located in Asia (represented by pink nodes). There are four distinct collaborative clusters: (1) Malaysia, Pakistan, USA, India, and Singapore; (2) Italy, South Korea, and China, (3) Egypt and Saudi Arabia; and (4) Viet Nam and Japan.

Figures 12–14 depict collaborations between institutions, with partnership frequencies ranging from 4 to 23. In the lower-right corner of Fig. 12, the collaboration between the Chinese Academy of Sciences and the University of Chinese Academy

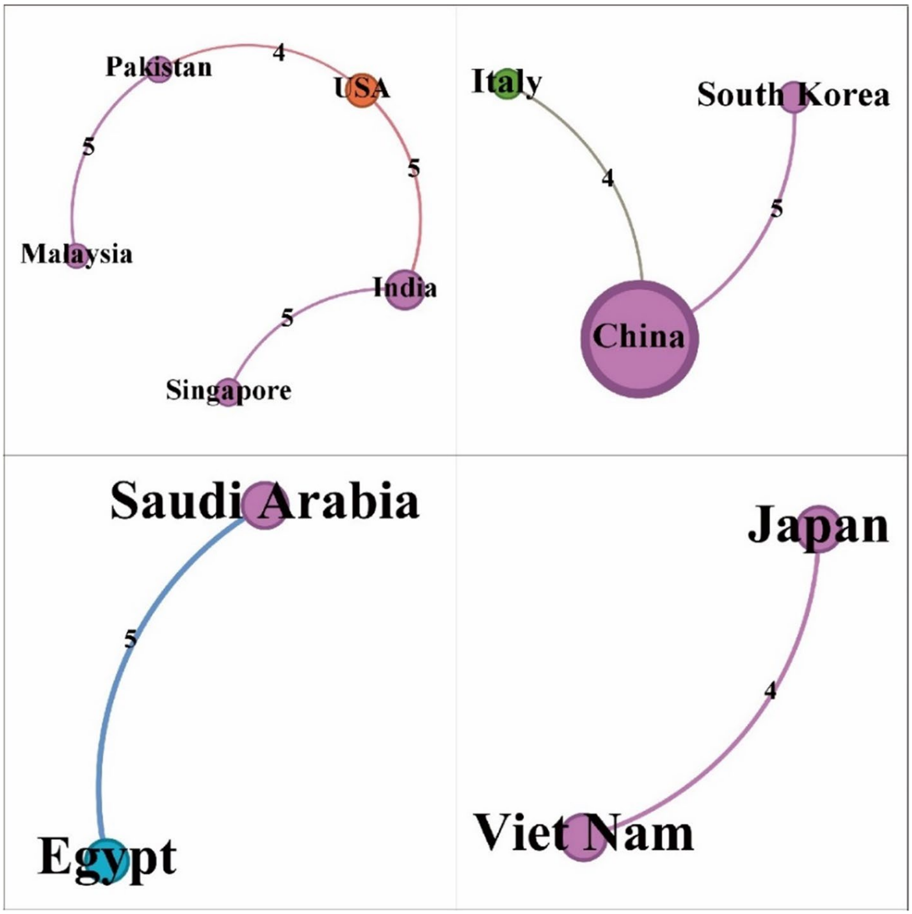

Fig. 11 Collaborations among countries/regions with 4 < = frequency < = 5

of Sciences is presented with a frequency of 23. Both institutions are based in China (indicated by pink nodes). In the lower-left corner of Fig. 12, the partnership between Shandong Jiaotong University and Shandong Normal University located in China is presented with a collaboration frequency of 12. Figure 12 also suggests two collaborative clusters formed by 5 institutions: (1) Harbin Institute of Technology, Peng Cheng Lab, and University of Warwick; and (2) Erasmus University and Bucharest University of Economic Studies. Figure 13 depicts four collaborative networks created by 10 institutions, each with a collaboration frequency of 5, including (1) Fudan University, East China Normal University, and Ryerson University; (2) University of Warwick and Peng Cheng Lab; (3) Vietnam National University, Electric Power University, and Ton Duc Thang University; and (4) Beijing Municipal Commission of Education and Beijing Jiaotong University. Figure 14 depicts 7 collaborative networks formed by 17 institutions with a collaboration frequency of 4. Among the 17 institutions, 7 are from China (pink nodes). In the collaborative networks, the cooperation between institutions from the same countries/regions was strong, as evidenced by collaborative connections such as (1) Chinese Academy of Sciences, Harbin Institute of Technology, and Peng Cheng Lab; (2) Ryerson University and York University, and 3) Vietnam National University and Electric Power University.

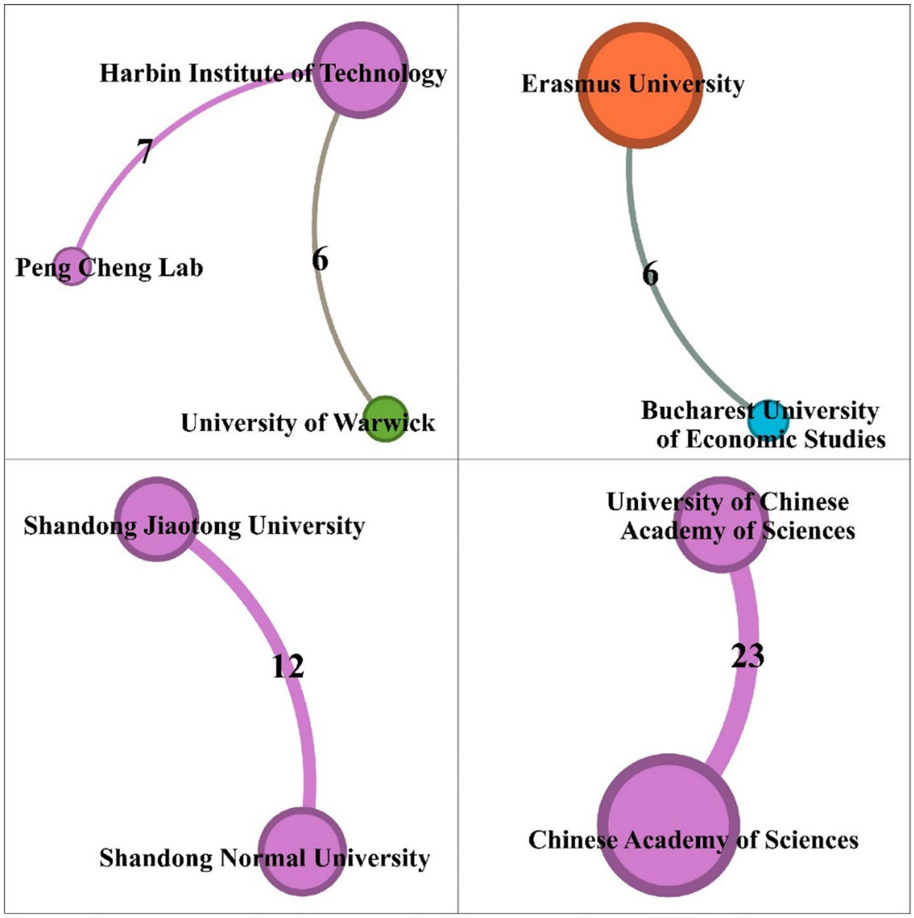

Fig. 12 Collaborations among institutions with 6 < = frequency < = 23

Topic modeling analysis

The STM results are presented in Table 7, which includes topic proportions, topic labels, and developmental trends. Of the 13 topics, the three most frequent topics encompassed *attention-based neural networks (ABNNs) for aspect mining* (13.66%), *graph-empowered ABSA* (11.48%), and *Granular ABSA for language structure extraction* (9.07%). The trend test results showed that *ABNNs for aspect mining*, *Graph-empowered ABSA*, *Granular ABSA for language structure extraction*, and *Transformer-based aspect sentiment analysis for text summarization* showed a significant and statistically strong upward trend. Two topics, including *Probabilistic modeling and performance evaluation for sentiment analysis*, and *Pattern-based aspect sentiment analysis in mobile products*, exhibited a statistically significant decline in trend. The other six topics did not demonstrate a statistically significant trend. Figure 15 provides a visual representation of the changing prominence of each topic.

Figure 16 displays topic correlations using a semi-parametric Gaussian approach. Each topic is denoted by a circle whose size corresponds to proportion. Dot lines, which indicate a positive correlation (> 0) between the two topics, link topics that are more likely to be discussed together in a paper. To compute correlation, a non-paranormal transformation of the topic proportions was carried out using a semi-parametric Gaussian

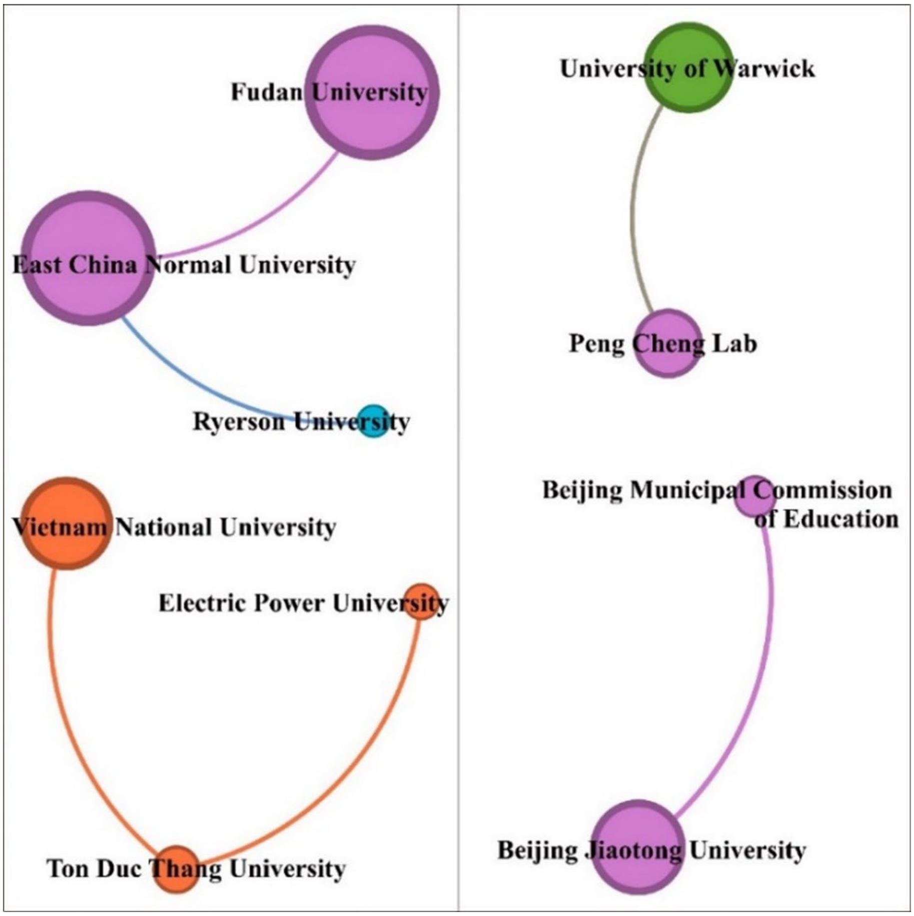

Fig. 13 Collaborations among institutions with frequency = 5

approach. A shorter association between two topics is indicative of a higher correlation. Negative correlations (≤ 0) indicate no association between the topics. The three distinct clusters are denoted by colored ellipses. G1 Cluster covers two topics: *Multi-criteria collaborative filtering for personalized recommendation systems* and *Customer experience analytics in e-commerce and tourism platforms*. G2 includes 3 topics: *Graph-empowered ABSA*, *ABNNs for aspect mining*, and *Contextual aspect modeling for corporate analytics*. G3 includes 3 topics: *Probabilistic modeling and performance evaluation for sentiment analysis*, *Pattern-based aspect sentiment analysis in mobile products*, and *Multilingual aspect sentiment analysis for education*.

Keyword co-occurrence analysis

The 1325 publications contained a total of 7229 keywords extracted from titles, abstracts, and author keywords with a total frequency of 15,826 overall. The top 50 keywords and their frequencies are shown in Table 8, representing the key ABSA research themes. The keyword "attention mechanism" was the most popular, followed by "machine learning", "deep learning", "BERT", "GCN", "neural network", and "CNN". We used 225 keywords for the co-occurrence analysis of keywords, and they appeared 5,087 times in the collected data or almost 33% of all the keywords. Figure 17 shows the keyword co-occurrence network that can be divided

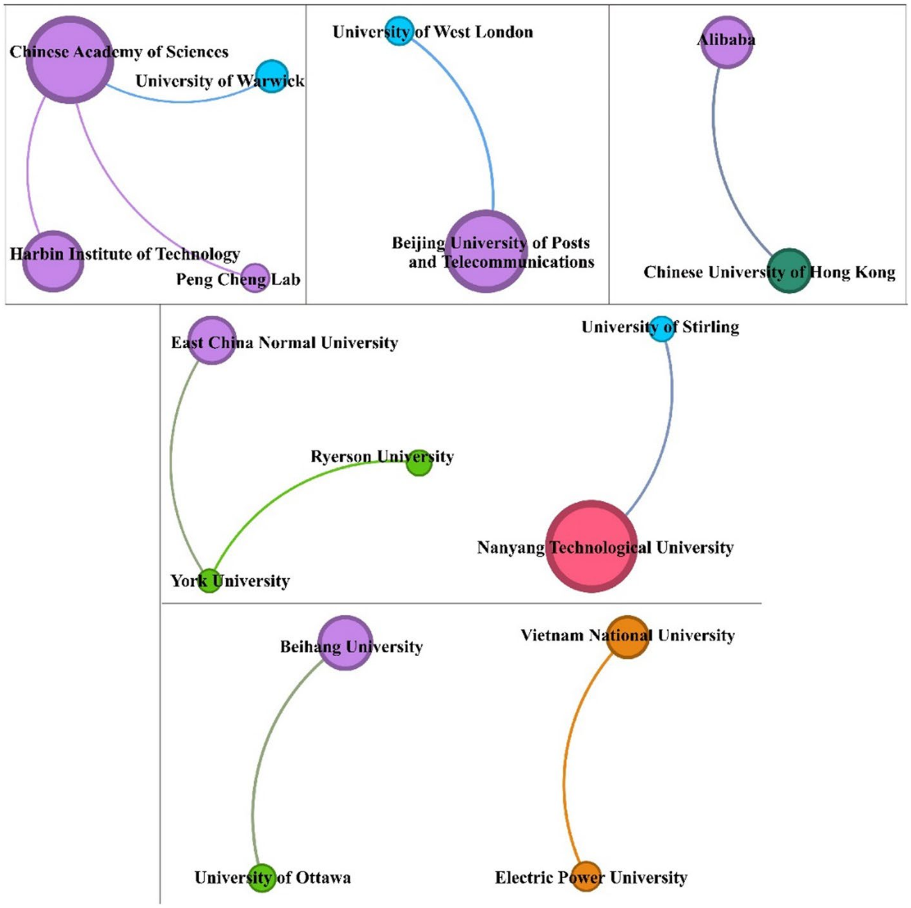

Fig. 14 Collaborations among institutions with frequency = 4

Table 7 Outcomes of the 13-STM, including topic proportions, topic labels, and developmental trends

Topic labels	Topic proportion	*p*-value	S	trend
ABNNs for aspect mining	13.66%	0.001	61	↑↑↑
Graph-empowered ABSA	11.48%	0	77	↑↑↑↑
Granular ABSA for language structure extraction	9.07%	0	81	↑↑↑↑
Customer experience analytics in e-commerce and tourism platforms	8.23%	0.3811	− 17	↓
Transformer-based aspect sentiment analysis for text summarization	7.91%	0.0007	63	↑↑↑↑
Multi-criteria collaborative filtering for personalized recommendation systems	7.50%	0.2736	− 21	↓
Probabilistic modeling and performance evaluation for sentiment analysis	7.36%	0.0001	− 71	↓↓↓↓
Pattern-based aspect sentiment analysis in mobile products	7.21%	0.0001	− 71	↓↓↓↓
Multilingual ABSA in domain-specific applications	6.70%	0.2284	23	↑
Multilingual aspect sentiment analysis for education	6.08%	0.5112	− 13	↓
Contextual aspect modeling for corporate analytics	5.60%	0.1546	27	↑
Domain-adaptive ABSA in legal and forensic computing	5.10%	0.2736	21	↑
Social media analytics and ABSA amidst covid-19	4.09%	1	− 1	↓

↑↑(↓↓), ↑↑↑(↓↓↓), ↑↑↑↑(↓↓↓↓): topic showing a significantly increasing (decreasing) tendencies

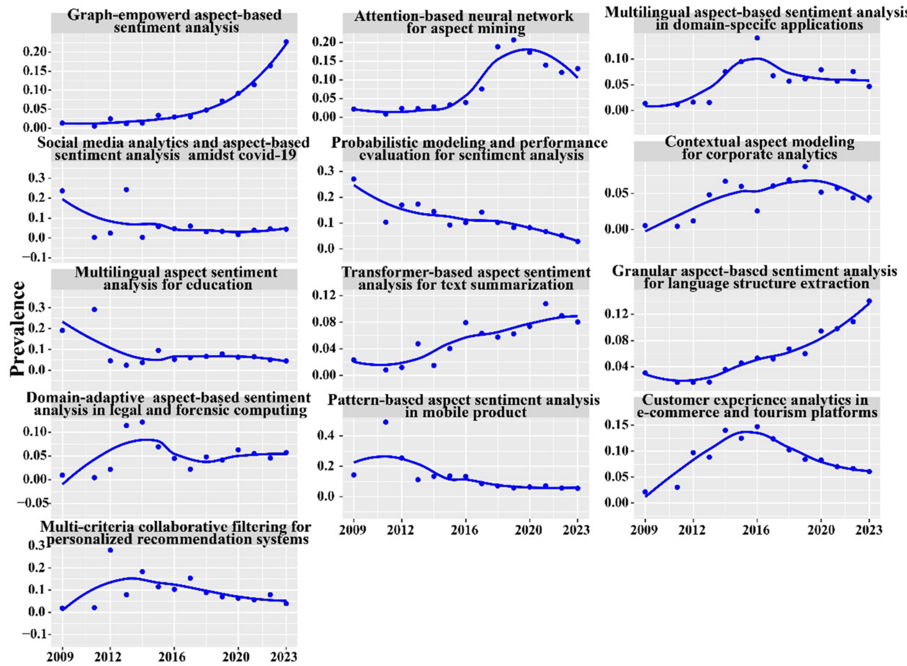

Fig. 15 Proportions of research topics by year

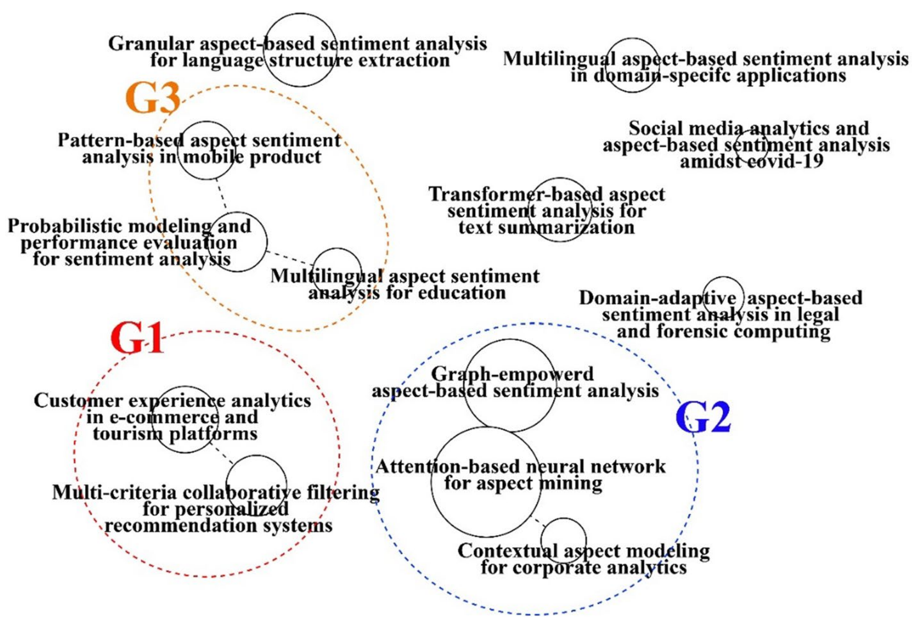

Fig. 16 Topic correlation visualization

into 13 communities, where the number of keywords is represented by the size of the nodes, and the co-occurrence frequency between keywords is shown by the thickness of the lines connecting the nodes. These 13 communities encompass ABSA research topics and methodologies, including Advanced ABSA Techniques (C1), Attention-Based ABSA Models (C2), Recommender Systems in ABSA (C3), Syntactic and Semantic Graph-Based Approaches

Table 8 Top 50 keywords based on word frequency

Rank	Keywords	Frequency	Rank	Keywords	Frequency
1	Attention mechanism	172	26	Text mining	40
2	Deep learning	169	27	Context	39
3	BERT	143	28	DNN	39
4	GCN	119	29	Opinion word	38
5	Neural network	110	30	Syntactic information	38
6	CNN	101	31	Recommender system	37
7	Machine learning	89	32	Sentiment prediction	37
8	Sentiment polarity	89	33	Data mining	36
9	Word embedding	86	34	Representation	36
10	Feature extraction	77	35	User review	36
11	LSTM	70	36	CRF	35
12	BiLSTM	69	37	Customer review	35
13	Online review	57	38	Part of speech	34
14	Multi task learning	52	39	pretrained language Model	34
15	Classification	48	40	Twitter	33
16	Dependency tree	48	41	Restaurant review	31
17	Self attention	46	42	Social medium	31
18	Task analysis	46	43	Attention network	29
19	Text analysis	46	44	Context word	28
20	Product review	45	45	Recurrent neural network	28
21	Transformer	44	46	Syntactic structure	28
22	Topic modeling	43	47	Dependency relation	27
23	SVM	42	48	Graph attention network	27
24	Semantics	41	49	Attention	26
25	LDA	40	50	Multi-head attention	26

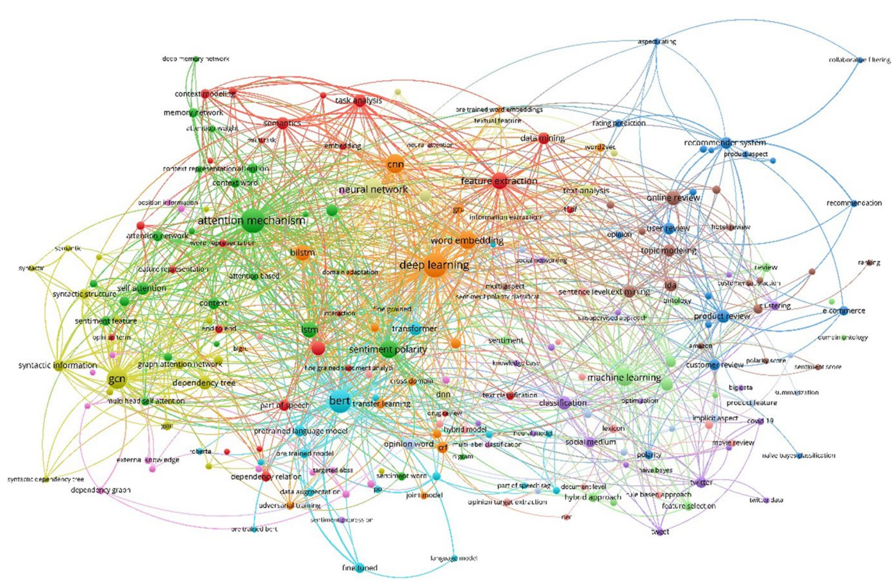

Fig. 17 Keyword community network (Accessed via https://drive.google.com/drive/folders/1M21LTVkZiixOrtAcmSa3nz4hfwkQVSb2?usp=drive_link)

Table 9 Keywords in each community

Community	Labels	Keywords
C1	Advanced ABSA Techniques	Feature extraction; multi task learning; task analysis; semantics; data mining; part of speech; dependency relation; context modeling; text classification; triplet extraction; end to end; word representation; syntactics; embedding; tfidf; feature representation; fine grained sentiment analysis; bit error rate; opinion term; multi task; reinforcement learning; drug review; global context; interaction; opinion word extraction
C2	Attention-Based ABSA	Attention mechanism; sentiment polarity; lstm; self-attention; context; representation; attention network; context word; attention; multi-head attention; memory network; attention based; gating mechanism; sentiment word; multi-head self-attention; multi-head; attention weight; context representation; interactive attention; capsule network; n gram; deep memory network; encoder decoder
C3	Recommender Systems in ABSA	Product review; recommender system; user review; customer review; e commerce; polarity; rating prediction; recommendation; sentiment orientation; opinion; review analysis; user opinion; user preference; product aspect; aspect rating; collaborative filtering; textual review; naive bayes classification; overall rating
C4	Syntactic and Semantic Graph-Based Approaches	Gcn; dependency tree; syntactic information; syntactic structure; graph attention network; syntactic dependency; gnn; contextual information; contrastive learning; fine grained; syntactic; dependency information; semantic; syntactic dependency tree; syntactic feature; aspect representation; linguistic feature; sentence representation; fusion mechanism
C5	Social Media ABSA	Classification; twitter; social medium; clustering; tweet; covid 19; opinion extraction; knowledge base; sentiment expression; social networking; neural model; optimization; social media analysis; big data; genetic algorithm; polarity detection; sentiment trend; twitter data; weakly supervised
C6	Pretrained Language Models in ABSA	Bert; transformer; pretrained language model; fine-tuned; pre-trained model; part of speech tagging; data augmentation; semi supervised; semi supervised learning; po; polarity classification; semantic feature; roberta; language model; part of speech tag; pre-training; labeling; pre-trained bert
C7	Deep Learning for ABSA	Deep learning; cnn; word embedding; bilstm; crf; recurrent neural network; gru; transfer learning; bidirectional gru; cross domain; word2vec; sequence labeling; adversarial training; joint model; domain adaptation; bigru; pre-trained word embeddings
C8	Topic Modeling and Decision Making in ABSA	Online review; topic modeling; lda; text mining; decision making; tripadvisor; user generated content; hotel review; multi aspect; visualization; amazon; customer satisfaction; multi criteria decision making; social network; sentiment score; polarity score; ranking

Table 9 (continued)

Community	Labels	Keywords
C9	Dependency Parsing and Semantic Information in ABSA	Dependency parsing; semantic relation; senticnet; dependency graph; external knowledge; position aware; sentiment information; long distance dependence; position information; sentiment knowledge; targeted absa; word dependency; affective knowledge; multi label classification; sentence; word level
C10	Lexicon-Based and Rule-Based Approaches in ABSA	Sentence level; lexicon; sentiwordnet; hybrid model; opinion target extraction; sentiment lexicon; feature level; rule-based approach; movie review; opinion target; document level; ner; neural attention; opinion summarization; sentence structure
C11	Machine Learning for ABSA	Machine learning; svm; restaurant review; hybrid approach; review; sentiment; ontology; feature selection; supervised learning; naive bayes; consumer review; domain ontology; ontology-based approach; restaurant dataset; supervised method
C12	Unsupervised Approaches in ABSA	Opinion word; implicit aspect; unsupervised learning; product feature; unsupervised method; explicit aspect; semantic similarity; review sentence; unsupervised approach; summarization; wordnet
C13	Neural Network-Based Text Analysis	Neural network; text analysis; dnn; sentiment prediction; textual feature; information extraction; information retrieval; representation learning; sentiment polarity classification; text representation; semantic analysis

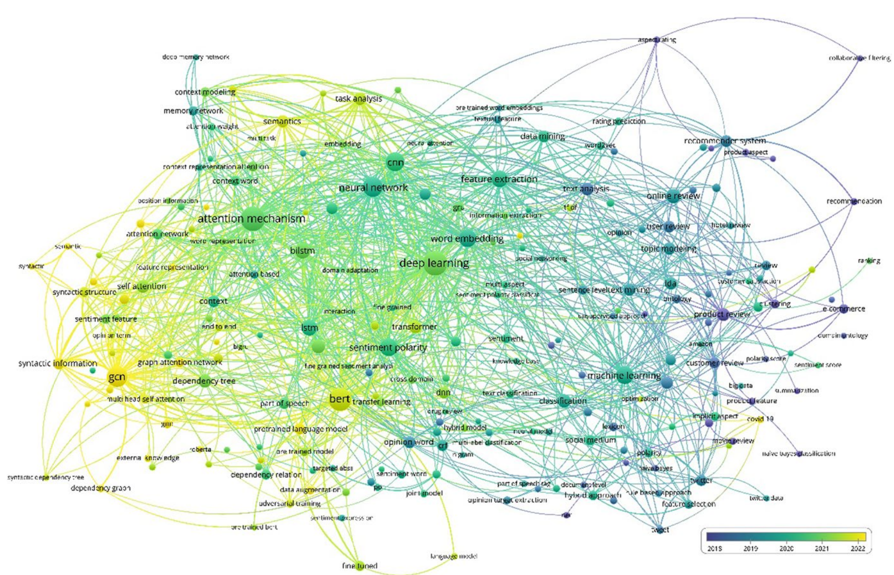

Fig. 18 Keyword evolution (Accessed via https://drive.google.com/drive/folders/16rFMcKuCoEGpRrGsstgwNBlx9bghDjiC?usp=drive_link)

(C4), Social Media ABSA (C5), Pretrained Language Models in ABSA (C6), Deep Learning for ABSA (C7), Topic Modeling and Decision Making in ABSA (C8), Dependency Parsing and Semantic Information in ABSA (C9), Lexicon-Based and Rule-Based Approaches in

ABSA (C10), Machine Learning for ABSA (C11), Unsupervised Approaches in ABSA (C12), and Neural Network-Based Text Analysis (C13).

Table 9 displays the top 20 keywords in each community in descending order, and Fig. 18 shows the evolution of keywords and communities. Four communities were mainly prevalent before 2019, including Lexicon-Based and Rule-Based Approaches in ABSA (C10), Topic Modeling and Decision Making in ABSA (C8), Recommender Systems in ABSA (C3), and Unsupervised Approaches in ABSA (C12). Around 2020, ABSA researchers have shown intensive interest in communities such as Social Media ABSA (C5) and Machine Learning for ABSA (C11). Around 2021, communities such as Attention-Based ABSA (C2), Deep Learning for ABSA (C7), Dependency Parsing and Semantic Information in ABSA (C9), and Neural Network-Based Text Analysis (C13) have been prevalent in the field of ABSA. From around 2022 till now, ABSA researchers have shown intensive interest in communities such as Advanced ABSA Techniques (C1), Syntactic and Semantic Graph-Based Approaches (C4), and Pretrained Language Models in ABSA (C6).

Research hotspots and trends

The analyses presented in Sects. "Topic modeling analysis" and Keyword co-occurrence analysis have shown that research topics and methods in ABSA are constantly evolving.

Specifically, the trend test analysis of the 13 topics, identified through topic modeling (Table 7 and Fig. 15), indicates that over the study period, four distinct research hotspots have emerged, signifying potential areas of future exploration. Firstly, the topic of *ABNNs for Aspect Mining* has exhibited a substantial and statistically robust upward trend, which underscores a pivotal shift in how ABSA research addresses the challenges of aspect extraction by leveraging the efficacy of ABNNs. These networks identify specific aspects within textual data by focusing on the most relevant parts of the text while filtering out irrelevant information, mimicking human cognitive processes. Attention mechanisms enhance interpretability and precision, particularly in scenarios where specific aspects are buried within lengthy, unstructured reviews [21, 40]. In e-commerce, this is critical for deriving actionable insights swiftly and accurately from customer feedback. Moreover, attention mechanisms' scalability for large-scale datasets is invaluable for big data applications. For example, in healthcare or financial services, attention-based models could extract sentiments tied to highly specific topics, such as patient care quality or investor sentiment, where precision and relevance are paramount. These implications suggest that attention mechanisms are setting a new benchmark for precision in ABSA, with transformative potential across diverse domains.

Secondly, the topic of *Graph-Empowered ABSA* demonstrates a statistically robust upward trend, signifying its growing importance. Graph-based approaches excel in addressing ABSA's complexity by capturing relationships and dependencies between words and phrases. By representing textual data as a graph, where nodes correspond to words or aspects and edges denote dependencies, these approaches enable a nuanced analysis of sentiment flows and contextual associations. For instance, in a sentence like "The screen is amazing, but the battery drains quickly", graph-based methods can accurately link positive sentiment to "screen" and negative sentiment to "battery". The significance of this approach lies in its ability to handle sentiment shifts and multi-aspect contexts to facilitate more precise, scalable sentiment analysis, making it particularly effective for multi-lingual and cross-cultural datasets. This has practical applications in global industries such as tourism and international marketing, where understanding nuanced and culturally specific sentiments is critical [41, 42].

Thirdly, the increasing emphasis on *Granular ABSA for Language Structure Extraction* signifies the growing demand for fine-grained analysis by allowing researchers and practitioners to dissect sentiments at a detailed level, moving beyond the generalization of sentiment across an entire review to identifying sentiments related to specific attributes such as “price” or “durability” [43, 44]. In practice, granular ABSA is transformative for industries like retail, where understanding customer pain points or preferences can directly inform product development [45, 46]. For example, while customers may appreciate a smartphone’s camera, dissatisfaction with its durability could signal a clear area for improvement. This level of specificity not only helps businesses prioritize product enhancements but also fosters stronger alignment with customer needs, ultimately driving competitive advantage [47].

Fourthly, the topic of *Transformer-Based Aspect ABSA for Text Summarization* demonstrates a significant and statistically robust upward trend. Transformers, such as BERT and GPT models, excel in tasks requiring nuanced contextual understanding [48, 49] by leveraging their bidirectional processing capability to grasp the relationship between aspects and sentiments even in complex sentences [50, 51]. For instance, in a review stating, “Although the sound quality is excellent, the headphones are uncomfortable for extended use”, transformers can accurately assign positive sentiment to “sound quality” and negative sentiment to “comfort”. This contextual understanding is invaluable for generating concise and accurate summaries of aspect-specific sentiments. The increasing adoption of transformers reflects a shift toward models capable of handling large volumes of user-generated content with precision., which is significant in areas such as social media monitoring and real-time sentiment analysis for brand reputation management, where actionable insights must be derived rapidly.

The keyword co-occurrence and the temporal analysis (Figs. 17 and 18) reveal a progression in research themes over time, with specific research thematic communities gaining prominence before and after certain years. For example, ABSA research before 2019 predominantly relied on lexicon- and rule-based methods [52, 53], which, while interpretable, were limited in handling complex linguistic structures and large datasets. The decline of these methods reflects their inability to scale with the growing complexity of real-world datasets. Post-2020, the shift toward machine learning models, particularly deep learning methods, marked a significant evolution in the field to uncover latent patterns in textual data that rule-based methods could not address. The rise of advanced ABSA techniques, such as fusion-, attention-, and graph-based approaches [54–57], aligns with the need to process more complex and diverse datasets. Similarly, the growing prominence of pre-trained language models [58] such as BERT since 2022 reflects their ability to set state-of-the-art performance benchmarks in ABSA. The dynamic nature of research focus is evident in the changing prevalence of techniques and methodologies. This evolution underscores the continuous integration of advanced technologies and collaborative approaches to enhance ABSA’s precision and efficacy in various areas [59–61]. For example, hybrid models combining graph-based and transformer-based techniques could provide even greater insights by merging structural and contextual understanding. The practical implication of these findings is that businesses and researchers can leverage more sophisticated tools and align their strategies with cutting-edge technologies to extract actionable insights, ensuring relevance and competitiveness in applications such as social media monitoring and customer sentiment analysis. For example, social media monitoring systems can use pre-trained models to analyze sentiment trends in real time, enabling brands to respond proactively to customer concerns.

Results of the topic correlation analysis presented in Fig. 16 unveil three emergent areas that collectively span a broad spectrum of applications, encompassing recommendation systems, customer experience analytics, corporate analytics, mobile product analysis, and multilingual education in ABSA. These trends impact practice by informing the development of innovative applications, such as multilingual customer service tools, adaptive recommendation engines, and cross-cultural sentiment analysis frameworks. Specifically, the emergence of research hotspots like multi-criteria recommendation systems and customer experience analytics within cluster G1 underscores the growing cross-domain applicability of ABSA such as integrating ABSA insights into multi-criteria recommendation systems to revolutionize e-commerce and tourism by providing personalized user experiences. The emphasis on personalization in recommendation systems aligns with the objective of enhancing user satisfaction, a concept further explored through customer experience analytics [62, 63]. Collaborative efforts in these areas have the potential to lead to more effective personalized recommendation systems within e-commerce and tourism platforms [64, 65] by understanding user sentiments to inform the refinement of recommendation algorithms, thus contributing to a holistic approach to enhancing user experiences, especially based on multiple criteria decision-making [66, 67]. In e-commerce, for instance, ABSA can enhance recommendation systems by integrating sentiment insights with traditional criteria like user ratings and purchase history. Similarly, in education, ABSA can analyze student feedback to identify patterns in course satisfaction, enabling institutions to tailor offerings to student needs. The growing prominence of attention mechanisms, transformers, and graph-based approaches within cluster G2 reflects a broader trend toward models that can manage increasing complexity and scale [68–70]. These advancements enable ABSA to move beyond traditional applications such as product reviews, into high-stakes domains like healthcare, where understanding patient sentiment could inform policy decisions, or finance, where investor sentiment analysis could guide market strategies. The three topics within cluster G3 can be jointly explored to develop a comprehensive ABSA framework capable of handling uncertain sentiments, identifying patterns across diverse aspects, and extending sentiment analysis to various language contexts in different sectors such as education [19]. Multilingual aspect sentiment analysis extends the application of ABSA to diverse linguistic contexts [71, 72], and has significant implications for global markets. By extending sentiment analysis to non-English datasets, businesses can better understand diverse customer bases. For example, an ABSA system capable of analyzing sentiments in Chinese and Arabic could provide insights for companies expanding into Asian and Middle Eastern markets. This is critical in regions where linguistic and cultural nuances significantly influence sentiment expression.

To sum up, the exploration of research hotspots and trends reveals the dynamic and evolving nature of ABSA research. Emergent research hotspots suggest a broad spectrum of applications, including recommendation systems, customer experience analytics, corporate analytics, and multilingual sentiment analysis. The growing prominence of attention mechanisms, transformers, and graph-based approaches enables ABSA to address complex real-world challenges across domains such as healthcare, finance, and education. These advancements provide researchers with robust tools to address complex datasets, while practitioners gain actionable insights that drive innovation in their respective areas.

Conclusion and future work

Conclusion

The increasing annual publication count signifies a growing interest in the field of ABSA research. Despite existing reviews on ABSA, there exists a gap in the literature concerning the discourse on the interactions between themes and research methodologies within ABSA research and the evolution of these issues over time. This work employs data-driven techniques to augment the insights of previous reviews by conducting a comprehensive analysis of ABSA research to outline the progression of research instruments, techniques, hotspots, and trends, and offer insightful recommendations for future research.

Utilizing various bibliometric metrics, such as the number of publications, total citation score, mean citation score, and H index, this study examines patterns, identifies pivotal sources, and recognizes key contributors in ABSA research. The research landscape in ABSA exhibits a consistent and upward trend in both the number of publications and citations over time. Neurocomputing, Knowledge-Based Systems, and IEEE Access are the three most relevant sources. China, India, and the United States stand out as the top three contributors, with China alone contributing nearly half of the ABSA research. Chinese Academy of Sciences, Nanyang Technological University, and Erasmus University are the most prolific institutions. SNA is employed to illustrate scientific collaboration among institutions, countries, and regions in ABSA research, revealing that heightened international collaboration correlates with enhanced performance and accelerated development.

This study delves into ABSA research topics and methodologies by examining ABSA trends and hotspots through keyword co-occurrence networks, community discovery, topic modeling analysis, and trend testing. Commonly employed terms in ABSA literature include "attention mechanism", "deep learning", "BERT", "GCN", "neural network", "CNN", and "machine learning". Identified hotspots encompass social media platforms, user comments, opinion mining for recommendations, and text summarization using ABSA. Furthermore, emerging research trends encompass attention-, transformer-, and graph-based strategies, pre-trained language models, deep learning technologies, hybrid approaches combining syntactic and semantic analysis, fine-grained ABSA techniques, and cross-domain ABSA methodologies.

Implications for practice and prospective avenues in ABSA research

The growing interest in adopting ABNNs signifies a growing recognition of their efficacy in identifying specific aspects within textual data by selectively focusing on relevant parts of input sequences, which, aided by attention mechanisms, enhances ABSA precision, particularly in aspect-specific contexts. Simultaneously, the increased use of graph-empowered ABSA reflects the increasing acknowledgment of graph-based approaches' abilities to represent textual data as graphs to capture complex relationships among different aspects, thus providing a more comprehensive ABSA. Granular ABSA, which emphasizes fine-grained ABSA at the aspect level by avoiding oversimplification and capturing nuanced sentiments related to different aspects, is increasingly recognized to contribute to a more detailed understanding of opinions. Additionally, the growing use of transformer-based ABSA for text summarization signals advancements in sequence-to-sequence capabilities to offer concise and informative sentiment outputs.

The emerging topic clusters demonstrate an upward trend in the focus on user-centric aspects by aligning personalization in recommendation systems with enhanced user satisfaction through customer experience analytics. Another rising interest lies in probabilistic modeling, pattern-based analysis, and multilingual ABSA, which reflects a collective effort to address uncertain sentiments, identify patterns, and extend ABSA to diverse language contexts. In addition, the emphasis on the integration of graph structures, attention mechanisms, transformers, graph-based approaches, pre-trained language models, and deep learning technologies within ABSA research, indicates an ongoing pursuit to enhance accuracy and efficiency through state-of-the-art techniques for a comprehensive ABSA. Future ABSA research can progress by integrating cutting-edge technologies and consistently aligning with evolving research interests to ultimately achieve comprehensive language comprehension in machine applications.

Limitations and future work

This study has limitations. First, its scope is confined to English-language publications sourced from the WoS database. We acknowledge that there might be ABSA-related articles in other languages or databases (e.g., Scopus) that are not included in our study. Future investigations could incorporate diverse literature databases. Second, while topic models excel in discerning thematic patterns within textual literature data, to achieve a more comprehensive understanding, future research could explore ways to incorporate text-mining technology with systematic qualitative analysis by developing methods capable of automated and systematic analysis of large-scale textual literature datasets.

Abbreviations

ABSA	Aspect-based sentiment analysis
SNA	Social network analysis
RQs	Research questions
PRISMA	Preferred reporting items for systematic reviews and meta-analyses
WoS	Web of Science
CPCI-SSH	Conference Proceedings Citation Index—Social Sciences and Humanities
SCI-Expanded	Science Citation Index Expanded
SSCI	Social Sciences Citation Index
TI	Title
TS	Topic Search
ATE	Aspect term extraction
STM	Structural topic modeling

P	Number of publications
PP	Percentage of total publications
TCS	Total citation score
MCS	Mean citation score
H	H-index
P (top10%)	Number of publications in top 10%
PP (top10%)	Proportion of publications in top 10%
C/R	Countries/regions
SIP	Single institution publications
MIP	Multiple institutions publications
PMIP	Percentage of multiple institutions publications
SCP	Single country/region publications
MCP	Multiple countries/regions publications
PMCP	Percentage of multiple countries/regions publications
ABNNs	Attention-based neural networks

Acknowledgements
Not applicable.

Author contributions
XC, HX contributed to the conception and design of the work, interpretation of data. XC, XT contributed to the data acquisition, curation, and analysis. FW, DZ, and HD have drafted the work and substantively revised it. All authors read and approved the final manuscript.

Funding
The research has been supported by the National Natural Science Foundation of China (No. 62307010) and Lam Woo Research Fund (LWP20019) and the Faculty Research Grants (DB23B2 and DB24A4) of Lingnan University. A grant from the Research Grants Council of the Hong Kong Special 11 Administrative Region, China(UGC/FDS16/E17/23).

Availability of data and materials
No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

Received: 29 September 2024 Accepted: 9 January 2025
Published online: 19 February 2025

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