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REVIEW

# Cognitive-Inspired Deep Learning Models for Aspect-Based Sentiment Analysis: A Retrospective Overview and Bibliometric Analysis

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**Abstract**
As cognitive-inspired computation approaches, deep neural networks or deep learning (DL) models have played important roles in allowing machines to reach human-like performances in various complex cognitive tasks such as cognitive computation and sentiment analysis. This paper offers a thorough examination of the rapidly developing topic of DL-assisted aspect-based sentiment analysis (DL-ABSA), focusing on its increasing importance and implications for practice and research advancement. Leveraging bibliometric indicators, social network analysis, and topic modeling techniques, the study investigates four research questions: publication and citation trends, scientific collaborations, major themes and topics, and prospective research directions. The analysis reveals significant growth in DL-ABSA research output and impact, with notable contributions from diverse publication sources, institutions, and countries/regions. Collaborative networks between countries/regions, particularly between the USA and China, underscore global engagement in DL-ABSA research. Major themes such as syntax and structure analysis, neural networks for sequence modeling, and specific aspects and modalities in sentiment analysis emerge from the analysis, guiding future research endeavors. The study identifies prospective avenues for practitioners, emphasizing the strategic importance of syntax analysis, neural network methodologies, and domain-specific applications. Overall, this study contributes to the understanding of DL-ABSA research dynamics, providing a roadmap for practitioners and researchers to navigate the evolving landscape and drive innovations in DL-ABSA methodologies and applications.

**Keywords** Deep learning · Aspect-based sentiment analysis · Bibliometric analysis · Topic modeling · Social network analysis

## Introduction

### Deep Learning for Aspect-Based Sentiment Analysis

Cognitive computing, with the aim of simulating or better understanding the biological cognitive systems of human beings to resolve complicated problems and integrate human intelligence into machines at scale, has marked a new era of computing [1, 2]. As cognitive-inspired computation technologies, deep neural networks (DNNs) are considered increasingly essential in fields such as cognitive computation and sentiment analysis [3]. Aspect-based sentiment analysis (ABSA) is a specialized branch of sentiment analysis [4] focusing on analyzing sentimental expressions toward specific aspects or attributes in texts, such as products, services, or topics [5, 6]. Unlike traditional sentiment analysis, which provides a general sentiment polarity for an entire document or sentence, ABSA offers a more granular understanding by attributing sentiments to individual aspects or entities mentioned within the text [7]. This nuanced approach enables organizations to gain deeper insights into customer opinions, product reviews, and public sentiment toward various aspects of interest [8].

In the realm of ABSA, researchers and practitioners employ a variety of methods and technologies to extract sentiment information from textual data. These methods encompass a spectrum of methods including rule-based and machine learning algorithms [9, 10]. Rule-based techniques depend on pre-established guidelines and patterns

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to determine sentiment-bearing aspects and classify their associated sentiments [11]. Machine learning techniques, on the other hand, leverage statistical models and algorithms to automatically learn patterns and relationships from labeled data, enabling more flexible and scalable sentiment analysis [12]. Common machine learning approaches in ABSA include supervised learning, where models are trained using labeled data to forecast sentiment labels for cases yet to be encountered, and unsupervised learning, which involves clustering and topic modeling to uncover latent sentiment patterns within text [13].

With the proliferation of large-scale textual data and the growing complexity of sentiment analysis tasks, deep learning (DL) has emerged as a powerful paradigm for advancing ABSA research [14]. As cognitive-inspired computation approaches, DL techniques, characterized by neural network architectures with multiple layers of abstraction, offer unparalleled capabilities in a variety of complicated cognitive tasks, including natural language processing (NLP) [15, 16]. In the context of ABSA, DL models can effectively capture subtle nuances in sentiment expressions across diverse domains and textual modalities [17, 18]. Moreover, DL frameworks enable end-to-end learning, where models automatically learn feature representations from data without the need for handcrafted features or domain-specific knowledge [19]. This capability makes DL particularly well-suited for ABSA tasks, where the identification of sentiment-bearing aspects and the interpretation of contextual nuances are paramount [20]. As a result, the increasing importance of DL for ABSA (DL-ABSA) research is evident, with researchers leveraging cutting-edge neural networks to push the boundaries of sentiment analysis and unlock new opportunities for understanding human opinions and preferences [21, 22].

## Cognitively and Biologically Inspired Basis of DL-ABSA

Sentiment analysis, as an important component of affective computing, has developed into an interdisciplinary field between computer science, artificial intelligence (AI), cognitive neuroscience, etc., aiming at enabling intelligent systems to identify, infer/predict, and interpret human emotions [23]. The analysis of human emotion, which involves complex behavior, cognition, psychology, and physiology, is a challenge in cognitive computing. Research in cognitive science [24] has revealed the relevance of the human brain's cognitive processing system to emotions. For example, positive emotions, such as joy, contribute to the creation of innovative solutions for problem-solving; on the contrary, negative emotions, such as distress, may result in low performance in cognitive tasks [25]. According to [26], the study of the brain's cognitive functions provides opportunities for natural language comprehension. As a result, researchers have attached increasing importance to cognitive heuristic mechanisms and the application of human cognitive principles in various fields of NLP, including sentiment analysis and ABSA [27].

The recent development of cognitive-inspired computing, interactions, and systems is promising for changing how we live [28]. As cognitive-inspired computing approaches, DNNs are fundamentally inspired by human structure and function, which mimic the hierarchy and learning process of biological neural networks and have achieved success in various areas, including cognitive computation and sentiment analysis [3], by empowering machines with cognitive abilities to distinguish, explain, and express emotions and sentiments [29]. For example, [30] introduced a cognitive computing methodology based on big data analytics for sentiment analysis by adopting binary brain-storm optimization and fuzzy cognitive maps for feature selection and emotion classification, respectively. Inspired by the emotional processing mechanisms in cognitive neuroscience, [31] proposed a multi-level attention-bidirectional long short-term memory (LSTM) method based on cognitive limbic systems to analyze emotions within multimodal data [32]. Developed a cognitive awareness framework that transferred cognitively-oriented knowledge within multimodal data using attention-based fusion and classified emotions using LSTM sub-models.

## Review of DL-ABSA and its Relevant Topics

Performing a systematic review and analysis of papers in niche fields is a major means of obtaining a comprehensive understanding of the topic [33]. Numerous surveys and reviews of relevant material have previously been published. A thorough overview of ABSA was given by Truşcć and Frasincar [11], who also presented a categorization system for aspect extraction and highlighted important works with a focus on contemporary approaches. Bensoltane and Zaki [34] provided a thorough analysis of Arabic ABSA studies, highlighting the main obstacles that various strategies must face, as well as future research objectives and gaps in the body of literature. To map linkages between aspects, interactions, dependencies, and contextual-semantic correlations, and to anticipate the development of sentiment dynamics, Nazir et al. [21] addressed challenges related to aspect and sentiment extraction.

Several reviews focused on DL-ABSA. DL in ABSA was evaluated by Do et al. [35] for contextualizing approaches. The authors also included concerns pertaining to sentiment analysis and ABSA, as well as the task's overall structure and the challenges associated with it. In the examination of DL methods inside ABSA, Trisna and Jie [36] explored possible directions for further research. Benchmark datasets, assessment measures, and DL techniques were presented by Liu et al. [37] for ABSA.

However, this study's use of indicators differs from prior research which mostly used a narrative method. Technological, social, and business perspectives are driving the dynamic growth of the DL-ABSA sector, necessitating periodic reviews and meta-analyses employing bibliometric approaches. These investigations use a variety of methodologies that cover several modes, nodes, aspects, and levels and include bibliometrics, surveys, knowledge, information, and data analytics. It is possible that earlier research ignored elements that are now important. Moreover, there is limited discussion on how research methods relate to theme developments across time. With its probabilistic methodology, topic models are able to identify topics based on word co-occurrences, which makes them useful for assessing a variety of abstracts in a field [38]. They support scholars, particularly those just new to the field, by helping them navigate research paths and better understand changing research trends in specific areas.

## Research Aims and Questions

This global bibliometric mapping study aims to methodically investigate theoretical developments and the status of knowledge in the quickly developing topics of DL-ABSA. This research, which takes a wide view and covers the years 2016 to 2023, provides a comprehensive review of the birth and development of new fields and specializations. To illustrate the worldwide contributions of publishing sources, nations/regions, and institutions, we first use bibliometric indicators, including publication counts, total citations, and the H-index. These indicators are then employed to pinpoint facets of DL-ABSA research between 2016 and 2023. The second goal is to look for partnerships between organizations, nations, and areas by employing social network analysis (SNA) and visualization. Lastly, we use topic modeling and term co-occurrence analysis to look at DL-ABSA patterns and areas of focus. The following four research questions (RQs) were developed for this study based on earlier bibliometric research (e.g., [39, 40]).

RQ1: In the field of DL-ABSA, what are the patterns of publishing and citation along with the top sources, academic institutions, and geographic locations?

RQ2: In the field of DL-ABSA, how do contributors collaborate?

RQ3: Which main topics and areas of focus best describe DL-ABSA research?

RQ4: How can researchers further DL-ABSA research, and what directions should they take?

The significance and motivations for answering these RQs are as follows.

First, by examining annual numbers of publications and citations (RQ1), this study offers perspectives on the progression and evolution of DL-ABSA research. The growth in numbers suggests the increasingly active landscape of this field [41]. Recognizing major contributors and publication sources allows for a better understanding of the global research landscape of DL-ABSA, including channels for making contributions and key actors for fostering efficient academic exchange [42, 43].

Second, by visualizing the collaborative networks (RQ2), this study reveals the complex collaborations and connections among contributors in the field of DL-ABSA. This knowledge is important to identify leading and influential collaborative groups in knowledge exchange and resource sharing when conducting DL-ABSA research activities [44].

Furthermore, by using topic modeling and keyword analysis approaches (RQ3), this study reveals the thematic structure within the DL-ABSA publications [45], shedding light on the important areas of research and interdisciplinary research directions. Visualization of the developmental tendencies of topics allows researchers to keep up-to-date with research developments and evolutions [43] when planning scientific and technological activities related to DL-ABSA.

In addition, by exploring topic dynamics and communities (RQ3), this study provides insights into the development of DL-ABSA research priorities and informs researchers of the evolving trajectories and areas of ongoing concern [46]. This knowledge contributes to understanding the history and current status of this field, as well as predicting its future.

First, the findings reveal that DL-ABSA publications and citations constantly grew during the study period. Second, journals such as IEEE Access, Knowledge-Based Systems, and Neurocomputing are the most active in this field. Third, China, India, and the USA are the top three countries in publishing DL-ABSA studies, with China contributing to over 63% of publications and three of its institutions, namely, the Chinese Academy of Sciences, Wuhan University, and South China Normal University, ranked in the top list. Fifth, countries/regions and institutions showing high levels of international collaboration demonstrate high productivity and research impact. Sixth, terms/phrases such as "opinion," "graph," "dependency," "convolution," "neural network," and "attention mechanism" show high frequency in DL-ABSA publications. Furthermore, research topics such as "syntax and structure analysis for sentiment analysis," "categorization and identification for ABSA," "domain adaptation for sentiment analysis," "network and connectivity approaches for ABSA," and "ABSA in pharmacovigilance" received increasing attention during the study period. In addition, potential future directions include the strategic importance of syntactic analysis, neural networks, and domain-specific applications.

The contributions of this study are as follows: (1) present a quantitative analysis of DL-ABSA literature based on bibliometrics and topic models; (2) identify the annual numbers of publications and citations to better understand the progress and evolution of DL-ABSA; (3) discover active publication sources to highlight channels for publishing DL-ABSA studies; (4) reveal active contributors to share insights or develop collaborations; (5) visualize collaborations among contributors to identify the leaders in collaborative networks; (6) uncover research topics and emerging themes to understand previous, current, and future DL-ABSA research; and (7) present an analytical approach suitable for large-scale literature analytics to overcome the limitations of manual qualitative analysis.

## Research Methodologies

This section describes the research methodologies, which include database selection and retrieval, data processing and screening of the literature, and data analysis through topic models, bibliometrics, SNA, and keyword/phrase frequency analysis. Figure 1 shows the general research framework.

### Data Search

Web of Science (WoS) provided the data used in this study. We used four citation databases: "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)." The articles under examination were mostly concerned with the application of ABSA to textual materials. Publications pertaining to ABSA in areas including biological signal processing, audio, video, images, and other processing domains were excluded. We used a sophisticated search approach that allowed for keyword combinations utilizing Boolean operators ("AND" and "OR") to make the process of selecting articles easier. The search query is presented in Table 7 in the Appendix. Conference proceedings are given the same weight in this study as journal publications. Only articles

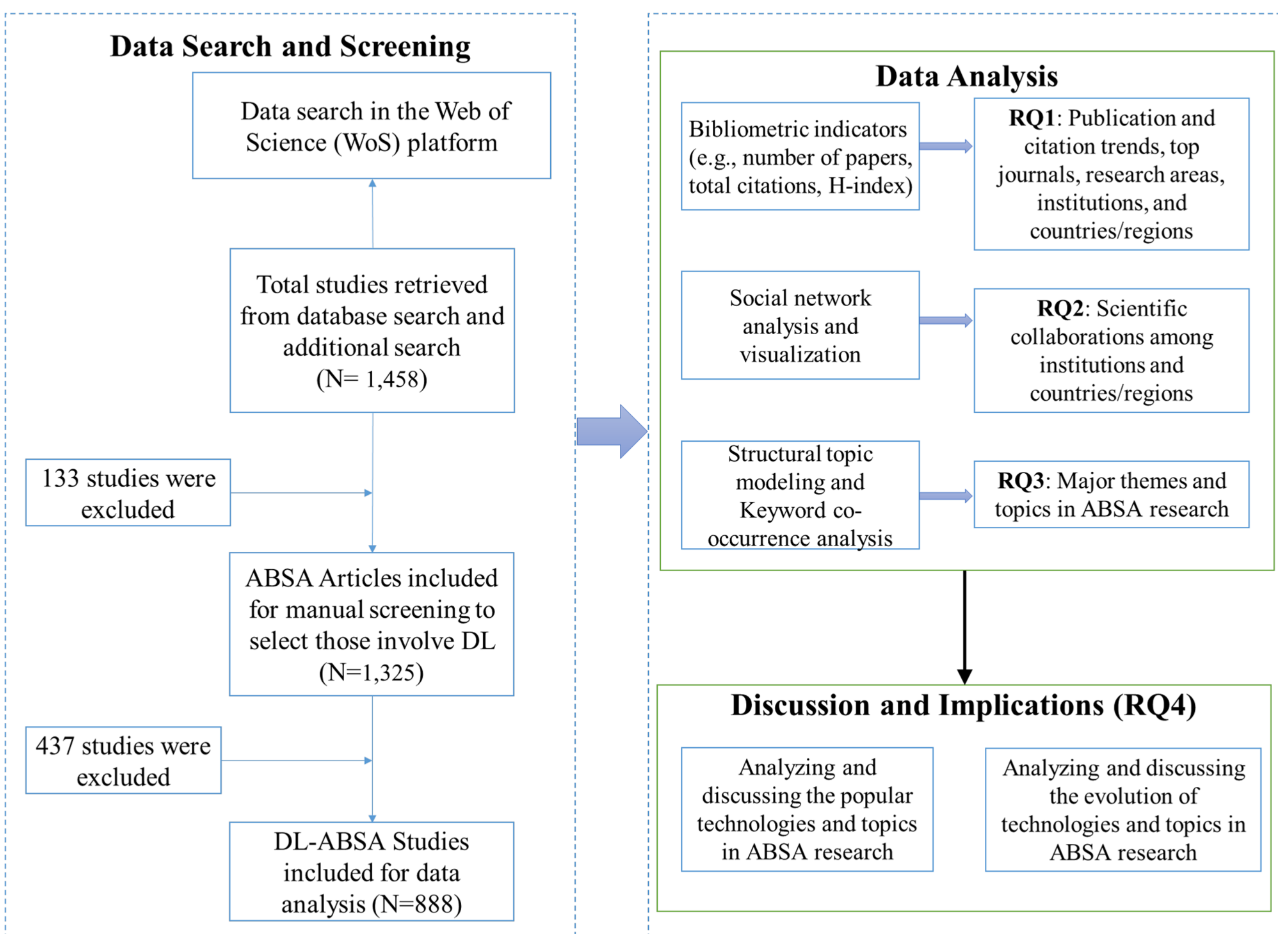


**Fig. 1** Flowchart of data search, screening, and analysis

published between January 2009 and the end of 2023 were taken into account in our research. These publications came in a variety of formats, such as "conference paper" and "article." All 1458 publications were gathered from the four databases listed above.

## Data Screening

A manual screening procedure comprising two stages was conducted to find papers closely related to DL-ABSA based on the original dataset of 1458 publications. In the first stage, each paper was examined to ensure relevance to ABSA. Specifically, the included document needed to address at least one of the following requirements: (1) aspect-based emotional polarity classification and analysis; (2) public opinion on certain facets of problems, occasions, or goods; (3) emotional grading and assessment based on aspects; (4) aspect classification, aspect word extraction, aspect category classification, and semantic feature extraction targeted at enhancing ABSA; and (5) the creation of methods or algorithms for ABSA. In this stage, 133 studies that met at least one of the criteria presented in Table 8 in the Appendix were excluded. Finally, 1325 ABSA papers were selected to be examined in the second stage.

In the second stage, each of the 1325 papers was examined to select those related to both DL and ABSA. Specifically, each paper on DL needed to address at least one of the following requirements: (1) DL models, (2) DL terminologies, and (3) DL frameworks. In this stage, 437 studies that met at least one of the following criteria were excluded: (1) mentions of traditional machine learning only, (2) lack of specificity, (3) conceptual discussions without method application, and (4) ambiguity in methodologies. A final dataset of 888 DL-ABSA publications from 2016 to 2023, including 521 journal articles and 367 conference papers, was used for data analysis.

## Data Analysis

To address the RQs, analyses were performed on 888 DL-ABSA articles spanning the years 2016 to 2023. These analyses covered the following aspects: (1) trends in publications and citations, (2) scientific cooperation, (3) major themes and topics, and (4) future avenues, employing bibliometrics, SNA, keyword/phrase frequency analysis, and topic modeling techniques.

We used metrics such as total citation count, average citations, H-index, number of publications in the top 10%, number of publications from single/multiple countries, and the percentage of single-country publications to evaluate publication outlets, fields of study, affiliations, and geographic locations in order to address RQ1. The spatial pattern of productivity was shown using GeoDa [47].

We used SNA in conjunction with Gephi [48] to answer RQ2 by creating a visual representation of scientific collaboration across affiliations, nations, and regions. SNA quantifies the relationships between things, such as persons, institutions, or nations, by using graphical networks to depict the structures that result from these interactions. In this architecture, quantifiable interactions are represented by edges, while entities are symbolized by nodes. Because of its visual clarity and ease of use, SNA is an excellent method for communicating the quantitative understanding of scientific collaboration among affiliations or nations.

We used topic modeling to find recurrent themes in response to RQ3. To improve the vocabulary, we employed the term frequency-inverse document frequencies and a filtering threshold of 0.05. Using the R stm [49] package, we used structural topic modeling (STM) to analyze two models of 15 and 18 topics from the DL-ABSA dataset, respectively, according to coherence and semantic distinctiveness criteria (Fig. 2). Following a comprehensive assessment by subject-matter specialists, who relied on their vast expertise in the field, the researchers finally decided on a 15-topic model. Considerations such as interpretability, efficacy, external validation, and semantic consistency went into making this choice. This methodology guaranteed that the model retained its interpretative value while generating topics.

The correlations between topics are estimated and visualized by the topicCorr function in the R huge package [50] to plot a graph with nodes and links indicating topics and correlations. In this study, the correlation between the maximum a posteriori estimates and the document–topic proportion distribution was calculated to obtain the marginal correlation of the variational distribution model. After setting the correlation threshold as 0, we used the topicCorr function to generate the correlative graph based on force-directed layout. A positive correlation ($>0$) between two topics indicates the possibility of discussing them in one publication. The shorter the link between two topics, the higher the correlation between them. Topics showing negative correlation ($<=0$) are disconnected. Finally, we followed [51] to add color ellipses in the correlation graph to highlight topic clusters (labeled G1 ~ G4).

To fully understand the important topics in the DL-ABSA inquiry, keyword/phrase frequency analysis was further included. Specifically, we used statistical analysis to determine the frequency of important terms or phrases. After that, these frequently recurring key terms and phrases were retrieved to provide the basis for further investigation into the primary approaches and topics in DL-ABSA.

As a reaction to RQ4, the analytical and visual findings were carefully reviewed and evaluated, taking into account a variety of factors including the most popular topics and research philosophies in each DL-ABSA theme. In addition, thorough analysis and discussion were carried out to

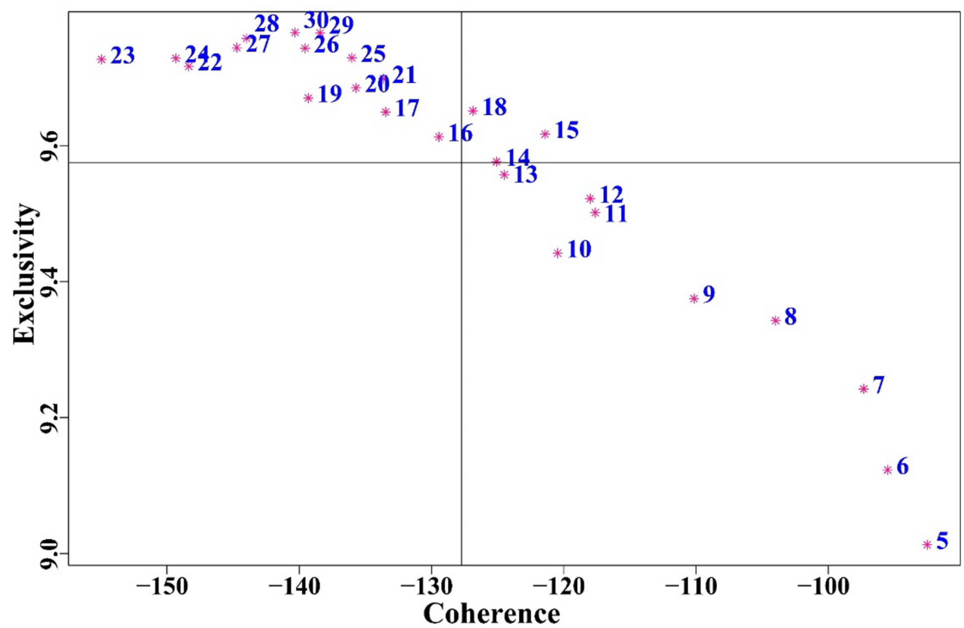


**Fig. 2** Semantic coherence and exclusivity values

elucidate the development of research approaches and topics in the DL-ABSA domain.

## Results and Analysis

### Publication and Citation Trends

As Table 1 shows, from 2016 to 2019, there were 195 research papers published on DL-ABSA, with a total citation value of 776 and a mean citation value of 3.98. These papers involved 744 authors from 354 affiliations across 249 countries/regions, averaging 3.82 authors and 1.82 affiliations per paper, and spanning 1.28 countries/regions per paper. From 2020 to 2023, the volume of research significantly increased, with 693 papers published, accumulating a total citation score of 12,245 and a mean citation score of 17.67. The number of authors also rose to 2812, representing 1255 affiliations from 878 countries/regions, with a slight increase in mean authors per paper to 4.06 and consistent mean affiliations per paper of 1.81, maintaining an average of 1.27 countries/regions per paper. Overall, from 2016 to 2023, the total number of papers reached 888, with a cumulative citation value of 13,021 and mean citation value of 14.66, involving 3556 authors from 1609 affiliations across 1127 countries/regions, with mean authors and affiliations per paper averaging at 4.00 and 1.81, respectively, and a mean of 1.27 countries/regions per paper. This suggests a significant expansion in both the volume and influence of this field's study across time, accompanied by increasing collaboration across institutions and nations.

**Table 1** Production analysis

| Indicators | 2016–2019 | 2020–2023 | 2016–2023 |
|---|---|---|---|
| Number of papers | 195 | 693 | 888 |
| Total citation score | 776 | 12,245 | 13,021 |
| Mean citation score | 3.98 | 17.67 | 14.66 |
| Total number of authors | 744 | 2812 | 3556 |
| Mean authors per papers | 3.82 | 4.06 | 4.00 |
| Total number of affiliations | 354 | 1255 | 1609 |
| Mean affiliations per papers | 1.82 | 1.81 | 1.81 |
| Total number of countries/regions | 249 | 878 | 1127 |
| Mean countries/regions per papers | 1.28 | 1.27 | 1.27 |

Over the span of eight years, from 2016 to 2023, research on DL-ABSA experienced substantial growth in both the number and corresponding citations (Fig. 3). The trend shows progressive growth, with a notable surge from 2019 onwards. In 2019, 118 papers were published, accumulating 644 citations. By 2023, this had risen to 196 papers and 3927 citations. Particularly noteworthy is the significant increase in citations from 2020 onwards, with 131 papers published in 2020 amassing 1398 citations. By 2022, the number of papers reached 201, with a staggering 4215 citations. This data reflects a robust and escalating interest in DL-ABSA research over the years, highlighting its growing importance and impact within the academic community.

The increase in the number and impact of DL-ABSA studies can be explained by improved abilities in processing and understanding complicated texts, as well as fine-tuning tasks on small samples due to the availability of

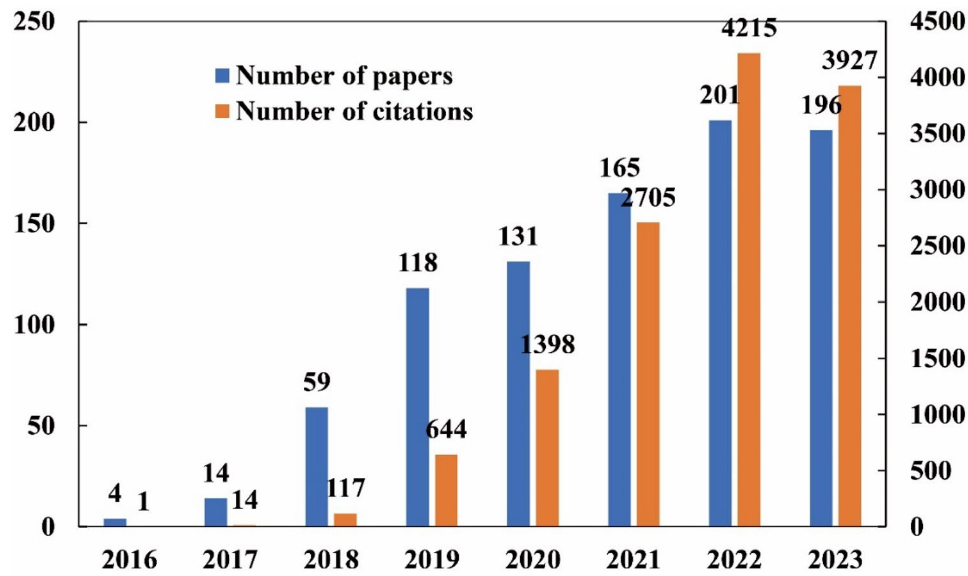


**Fig. 3** Annual number of publications and citations

advanced neural network models such as convolutional neural networks (CNNs), LSTM networks, and, more recently, pre-trained language models such as bidirectional encoder representations from transformers (BERTs) and generative pre-trained (GPT) models [16, 52, 53]. Furthermore, the rapid increase in user-generated content provides rich data sources for DL-ABSA to achieve efficient and robust model training and benchmarking [54, 55]. In addition, the growing need for using DL-ABSA approaches to understand customers' opinions and sentiments toward different aspects of products and services for optimized decision-making is driving the development of effective DL-ABSA applications and systems [13, 21, 56].

We also present a systematic analysis of 25 papers ranked among the top 20 lists according to number of total citations and annual citations [57] to understand the research issues, technologies used, and purpose and effectiveness of technology used in these studies. The results are shown in Table 9 in the Appendix. The use of different embeddings (e.g., [58–63]) highlights the importance of initializing models with rich semantic representations. While BERT's contextual embeddings show superior performance, traditional embeddings such as GloVe and Word2Vec still play a crucial role in non-BERT models. Also, the deployment of advanced architectures such as graph convolutional networks (GCNs), LSTMs, and CNNs (e.g., [64–71]) underscores the complexity of ABSA tasks. Each architecture addresses different aspects of sentence representation, from capturing dependencies (e.g., GCNs) to long-term contextual information (e.g., LSTMs) and local feature extraction (e.g., CNNs).

Moreover, the emphasis on attention mechanisms (e.g., [72–74]) reveals their critical role in ABSA. They allow models to selectively focus on important parts of the input, thereby improving the accuracy of aspect and sentiment classification. Furthermore, the consistent use of Adam Optimizer and regularization techniques such as L2 regularization (e.g., [75–80]) across various models indicates their importance in achieving stable and generalizable performance. In addition, techniques such as interactive multi-task learning networks and domain-specific embeddings (e.g., FastText) (e.g., [81, 82]) highlight the benefits of tailoring models to specific domains, which can significantly improve task performance. Overall, the technologies used in the top 25 DL-ABSA studies demonstrate a multifaceted approach to tackling the challenges of sentiment analysis at the aspect level, from leveraging advanced neural architectures to employing sophisticated optimization techniques. The integration of contextual embeddings, attention mechanisms, and domain-specific knowledge further underscores the importance of a holistic and adaptive approach in this field.

## Top Publication Sources and Research Areas

The statistical analysis of 888 research papers on DL-ABSA reveals a diverse landscape of publication sources and their corresponding impact (see Table 2). Most papers were released in IEEE Access (61 papers, 6.87% of total publications) and Knowledge-Based Systems (49 papers, 5.52%), followed by Neurocomputing (33 papers, 3.72%). The top three journals in publishing DL-ABSA research emphasized interdisciplinary topics, including AI and neural networks, and are published by reputable publishers (i.e., IEEE and Elsevier). These journals have also been identified as active sources in previous reviews on AI-related topics (e.g., [83, 84]). The results corroborate [35], which demonstrates the connection between sentiment analysis and AI-powered tools. The three journals were also included in the SSCI or SCI databases, with 5-year impact factors of 4.1, 8.6, and

**Table 2** Publication sources by production

| Publication sources | P | PP | TCS | MCS | H | P1 | PP1 |
|---|---|---|---|---|---|---|---|
| IEEE Access | 61 | 6.87% | 895 | 14.67 | 16 | 5 | 5.62% |
| Knowledge-Based Systems | 49 | 5.52% | 1101 | 22.47 | 19 | 8 | 8.99% |
| Neurocomputing | 33 | 3.72% | 519 | 15.73 | 14 | 3 | 3.37% |
| International Joint Conference on Neural Networks | 26 | 2.93% | 50 | 1.92 | 3 | 0 | 0.00% |
| Applied Intelligence | 24 | 2.70% | 267 | 11.13 | 8 | 1 | 1.12% |
| Applied Sciences-Basel | 19 | 2.14% | 137 | 7.21 | 4 | 1 | 1.12% |
| AAAI Conference on Artificial Intelligence | 18 | 2.03% | 893 | 49.61 | 12 | 7 | 7.87% |
| The Association for Computational Linguistics | 18 | 2.03% | 1569 | 87.17 | 14 | 13 | 14.61% |
| Conference on Empirical Methods in Natural Language Processing | 18 | 2.03% | 731 | 40.61 | 13 | 6 | 6.74% |
| Journal of Intelligent and Fuzzy Systems | 14 | 1.58% | 107 | 7.64 | 3 | 1 | 1.12% |
| Journal of Supercomputing | 14 | 1.58% | 37 | 2.64 | 4 | 0 | 0.00% |

*P and PP* number and proportion of publications, *TCS* total citations, *MCS* mean citations, *H* H-index, *P1 and PP1* number and proportion of publications in top 10% rank

6, respectively. As [85] shows, studies published in journals with high impact factors are generally of high quality with wide influence [86]. Also claimed that researchers may wish to publish their results in prestigious conferences or journals to have a higher possibility of receiving funding support.

The Association for Computational Linguistics had the highest total citation score (1569), mean citation score (87.17), and H-index (14), indicating its significant influence in the field. However, regarding the number of publications in the top 10% by rank, IEEE Access, Knowledge-Based Systems, and AAAI Conference on Artificial Intelligence stand out, with proportions of 5.62%, 8.99%, and 7.87%, respectively, showcasing their prominence in impactful research dissemination. Overall, this analysis underscores the importance of considering both the quantity and quality of publications in understanding the scholarly contributions within the domain of DL-ABSA.

The statistical analysis of 888 research papers focusing on DL-ABSA reveals the distribution of publications across various sources over different time periods (see Fig. 4). From 2016 to 2019, there was a relatively lower volume of research, with notable contributions from journals such as IEEE Access and The Association for Computational Linguistics. From 2020 to 2023, there was a substantial increase in research output, with conferences and journals such as the AAAI Conference on Artificial Intelligence, The Association for Computational Linguistics, the Conference on Empirical Methods in Natural Language Processing, and Knowledge-Based Systems exhibiting significant growth in the number of papers published. Notably, Applied Intelligence and IEEE Access also saw a considerable rise in contributions during this later period. Overall, this analysis highlights the evolution of research efforts in DL-ABSA,

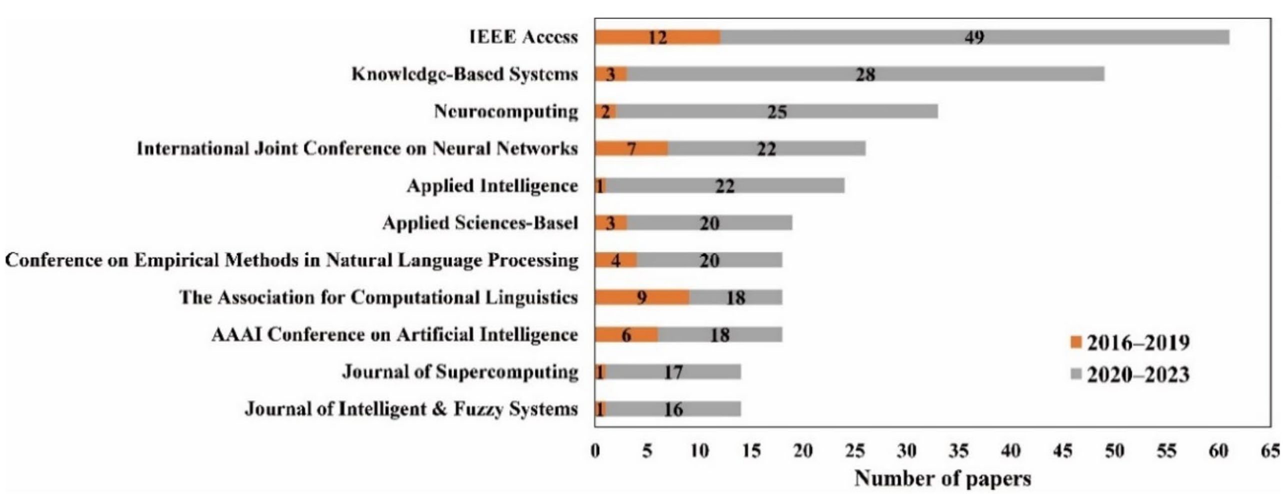


**Fig. 4** Top publication sources

with a notable surge in publications from 2020 onwards across various publication sources.

## Top Institutions and Countries/Regions

The statistical analysis of 888 research papers on DL-ABSA reveals the dominant contributions from institutions come primarily from China (see Table 3), with the Chinese Academy of Sciences leading with 33 publications, comprising 3.72% of the total. Chinese institutions, including South China Normal University and Wuhan University, exhibit high rates of collaboration, with a significant proportion of publications coming from multiple institutions, indicating strong research networks within China. Notably, Nanyang Technological University also emerges as a prominent contributor, ranking fourth in terms of the number of publications, but securing the highest total and mean citation values, reflecting its impactful research output. Overall, this analysis underscores the substantial presence of Chinese institutions in DL-ABSA research, along with notable contributions from selected international institutions such as Nanyang Technological University.

The statistical analysis of 888 research papers on DL-ABSA indicates a diverse spectrum of institutional contributions across two distinct time periods (see Fig. 5). Notably, Chinese institutions feature prominently in both sets, with the Chinese Academy of Sciences leading with 24 papers published from 2020 to 2023, followed closely by Wuhan University and South China Normal University, each with 21 and 22 papers, respectively. Nanyang Technological University emerges as a significant contributor with 13 papers during the same period. Furthermore, institutions such as East China Normal University, Fudan University, and Shandong Jiaotong University demonstrate considerable growth in research output from 2016 to 2019 to 2020 to 2023, underscoring the evolving landscape of collaborative research efforts in this field. Overall, these findings highlight the active engagement of various institutions in advancing knowledge and understanding within the realm of DL-ABSA.

The statistical analysis of 888 research papers on DL-ABSA demonstrates global engagement, with China leading in both the number of publications and total citation score (see Table 4). Chinese institutions contributed significantly with 562 papers, accounting for 63.29% of the total publications and amassing a total citation score of 8136. USA, India, and Singapore also made substantial contributions, with notable collaborations between multiple countries/regions, particularly evident in Singapore, with 70.73% of its publications being collaborative. Furthermore, countries such as the UK, Australia, and Germany also demonstrated significant involvement in research efforts. This analysis underscores widespread interest and collaboration across various countries/regions in advancing the understanding and application of DL-ABSA, highlighting its global importance in academic research. Figure 6 illustrates the geographical distribution of published documents by country/region, using graduated colors to indicate the number of published documents; darker colors indicate a larger number of published documents. It reveals that China exhibits the highest engagement in DL-ABSA research.

The statistical analysis of 888 research papers on DL-ABSA highlights a significant surge in research activity, particularly from 2020 to 2023 (see Fig. 7). China emerges as the predominant contributor with 562 papers, indicating a substantial focus on this topic. India follows with 72 papers, demonstrating a notable increase compared to earlier years. The USA, though still actively engaged, shows a more modest growth trajectory with 65 papers. Other countries such as Singapore, the UK, and Australia also show

**Table 3** Productive institutions

| Institutions | P | PP | SIP | MIP | PMIP | TCS | MCS | H | P1 | PP1 |
|---|---|---|---|---|---|---|---|---|---|---|
| Chinese Academy of Sciences | 33 | 3.72% | 2 | 31 | 93.94% | 305 | 9.24 | 11 | 2 | 2.25% |
| South China Normal University | 24 | 2.70% | 12 | 12 | 50.00% | 216 | 9.00 | 6 | 2 | 2.25% |
| Wuhan University | 24 | 2.70% | 12 | 12 | 50.00% | 361 | 15.04 | 6 | 3 | 3.37% |
| Nanyang Technological University | 23 | 2.59% | 6 | 17 | 73.91% | 1181 | 51.35 | 14 | 8 | 8.99% |
| University of Chinese Academy of Sciences | 22 | 2.48% | 1 | 21 | 95.45% | 187 | 8.50 | 7 | 2 | 2.25% |
| Beijing University of Posts and Telecommunications | 21 | 2.36% | 7 | 14 | 66.67% | 171 | 8.14 | 8 | 1 | 1.12% |
| Harbin Institute of Technology | 21 | 2.36% | 3 | 18 | 85.71% | 446 | 21.24 | 7 | 5 | 5.62% |
| Shandong Jiaotong University | 17 | 1.91% | 4 | 13 | 76.47% | 159 | 9.35 | 8 | 0 | 0.00% |
| Shandong Normal University | 17 | 1.91% | 4 | 13 | 76.47% | 133 | 7.82 | 8 | 0 | 0.00% |
| East China Normal University | 15 | 1.69% | 2 | 13 | 86.67% | 190 | 12.67 | 6 | 1 | 1.12% |
| Fudan University | 15 | 1.69% | 7 | 8 | 53.33% | 494 | 32.93 | 9 | 3 | 3.37% |

The same as Table 2 except for three indicators (*SIP* single institution publications, *MIP* multiple institutions publications, *PMIP* percentage of multiple institutions publications)

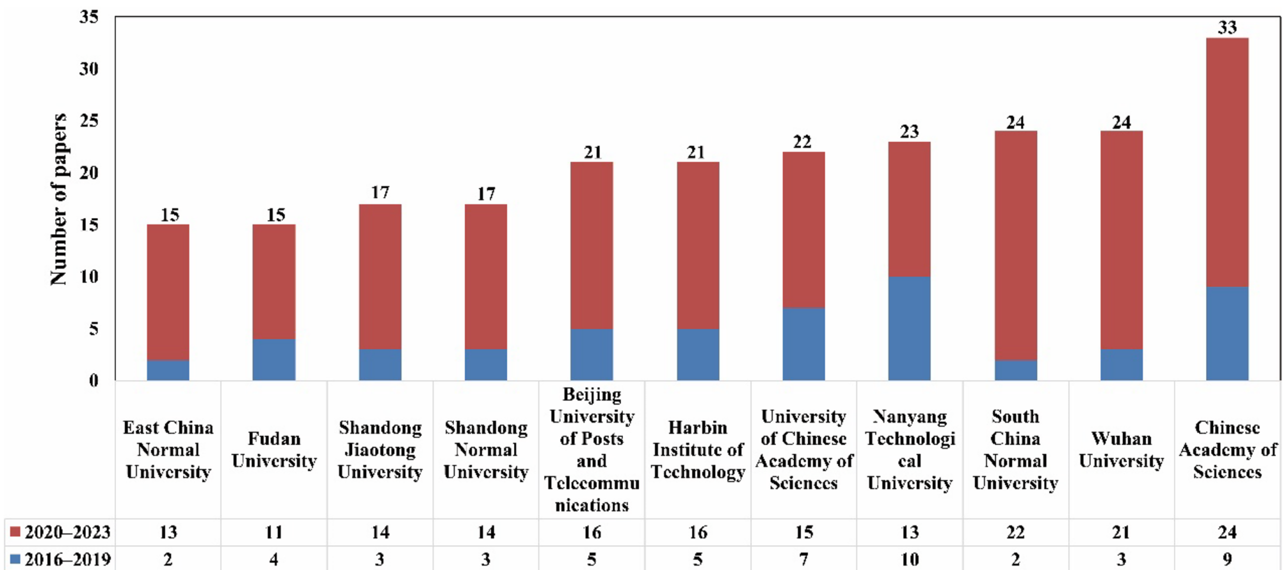


**Fig. 5** Top institutions

varying levels of engagement, reflecting a global interest in advancing DL-ABSA. Overall, the data suggest a robust and diversified research landscape, with contributions from various countries driving advancements in this field.

The differences in research outputs between various countries and institutions can be attributed to research capabilities, funding, or policies that promote AI research [87]. For instance, the Chinese government has invested substantial funds in AI-related scientific activities as an important component of its strategic initiatives, such as the Next Generation Artificial Intelligence Development Plan (NGAIDP) launched on July 28, 2017. The goal of this plan is to improve the competitive advantages of national AI development and accomplish high levels of technological autonomy [88]. Furthermore, public policies have attached increasing importance to the intelligent development of various economic and social sectors through the promotion of next-generation AI promotion. Government support has encouraged large-scale NLP- and AI-related research projects such as DL-ABSA to be conducted in various Chinese institutions, for example, the Chinese Academy of Sciences, Wuhan University, and South China Normal University.

## Collaboration Analysis

Seven countries/regions are shown in Fig. 8, with cooperation frequencies ranging from 11 to 32. Three of these are found in Asia. Remarkably, the most robust cooperation was noted in 32 articles between the USA and China.

**Table 4** Most productive countries/regions

| C/R | P | PP | SCP | MCP | PMCP | TCS | MCS | H | P1 | PP1 |
|---|---|---|---|---|---|---|---|---|---|---|
| China | 562 | 63.29% | 431 | 131 | 23.31% | 8136 | 14.48 | 45 | 60 | 67.42% |
| India | 72 | 8.11% | 56 | 16 | 22.22% | 646 | 8.97 | 12 | 4 | 4.49% |
| USA | 65 | 7.32% | 20 | 45 | 69.23% | 2082 | 32.03 | 21 | 18 | 20.22% |
| Singapore | 41 | 4.62% | 12 | 29 | 70.73% | 1959 | 47.78 | 19 | 14 | 15.73% |
| UK | 28 | 3.15% | 7 | 21 | 75.00% | 712 | 25.43 | 12 | 6 | 6.74% |
| Australia | 25 | 2.82% | 2 | 23 | 92.00% | 176 | 7.04 | 5 | 1 | 1.12% |
| South Korea | 22 | 2.48% | 11 | 11 | 50.00% | 274 | 12.45 | 8 | 2 | 2.25% |
| Vietnam | 21 | 2.36% | 14 | 7 | 33.33% | 221 | 10.52 | 7 | 2 | 2.25% |
| Germany | 18 | 2.03% | 9 | 9 | 50.00% | 245 | 13.61 | 8 | 3 | 3.37% |
| Netherlands | 18 | 2.03% | 11 | 7 | 38.89% | 142 | 7.89 | 4 | 2 | 2.25% |
| Pakistan | 18 | 2.03% | 5 | 13 | 72.22% | 173 | 9.61 | 7 | 1 | 1.12% |

The same as Table 2 except for four indicators (*C/R* countries/regions, *SCP* single country/region publications, *MCP* multiple countries/regions publications, *PMCP* percentage of multiple countries/regions publications)

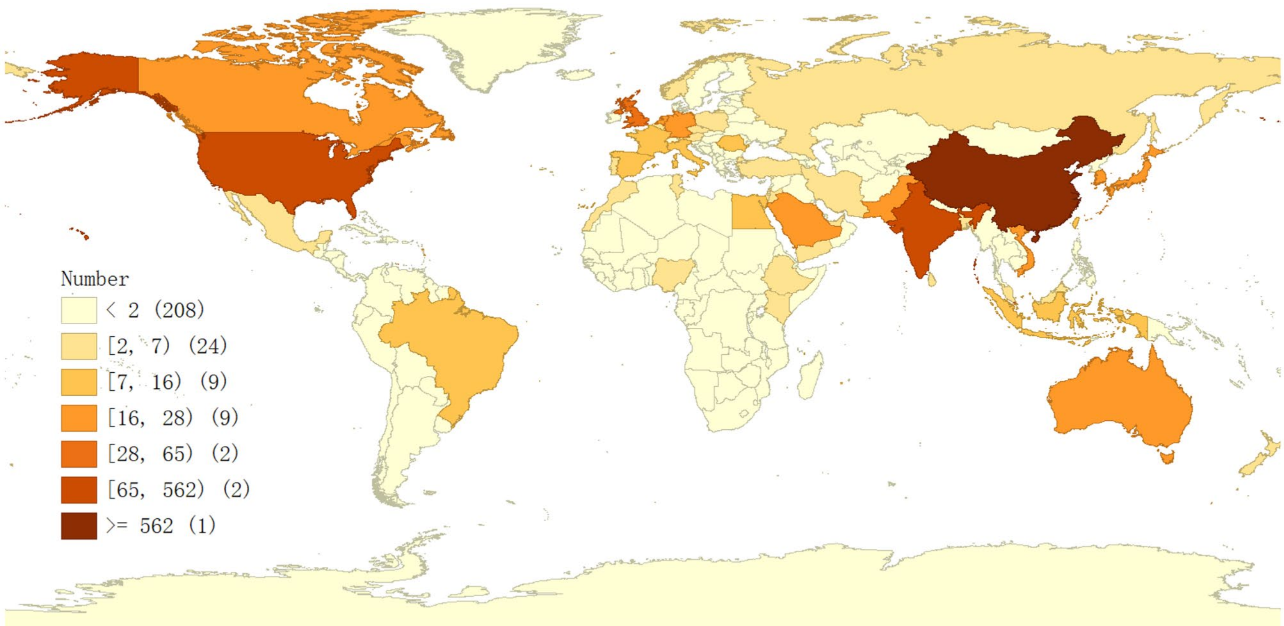


**Fig. 6** Geographic distribution

Subsequently, there were partnerships between China and the UK (18), Australia (18), Singapore (17), Canada (11), and Hong Kong (11). A total of 10 countries/regions are represented in Fig. 9, where partnership frequencies range from five to seven. Three are from Europe and seven are from Asia. These three collaborative clusters, including (1) India and Singapore, (2) the Netherlands and Romania, and (3) Pakistan, Saudi Arabia, South Korea, China, Japan, and Germany, showcase how closely they collaborate. Figure 10 presents collaborations between 15 countries/regions with three to four cooperating frequencies. Five collaborative clusters demonstrate the strong collaborative relationships that these 15 countries/regions maintain: (1) Singapore and the UK; (2) Saudi Arabia and Egypt; (3)

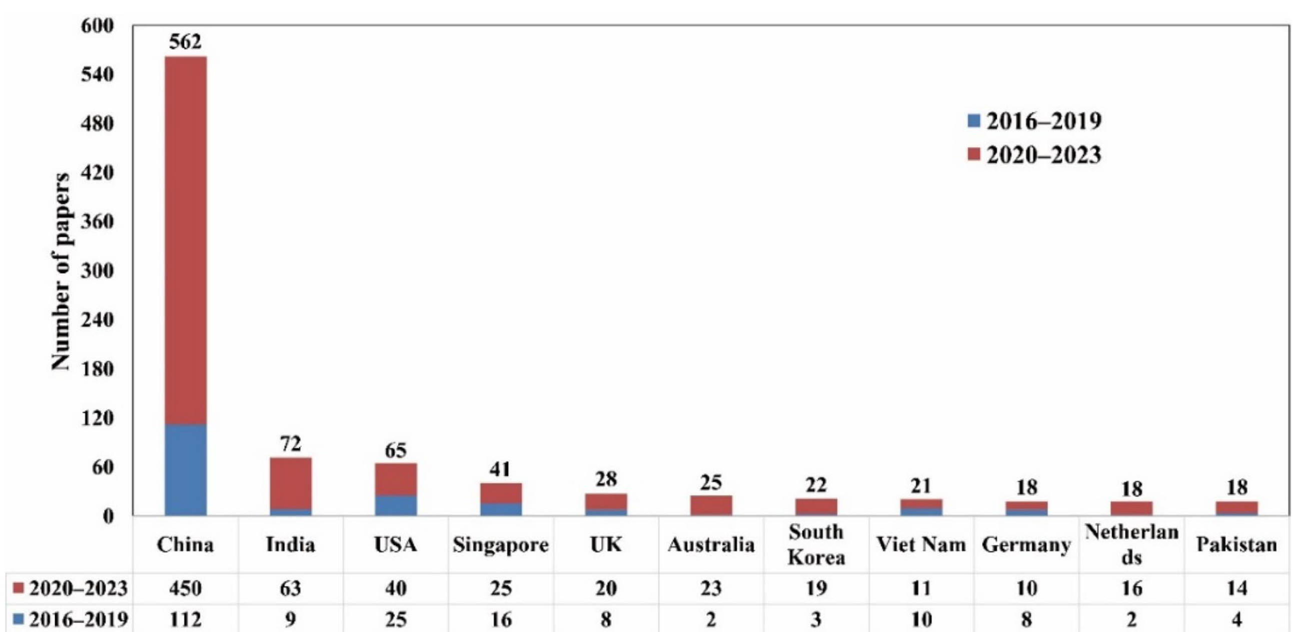


**Fig. 7** Top countries/regions

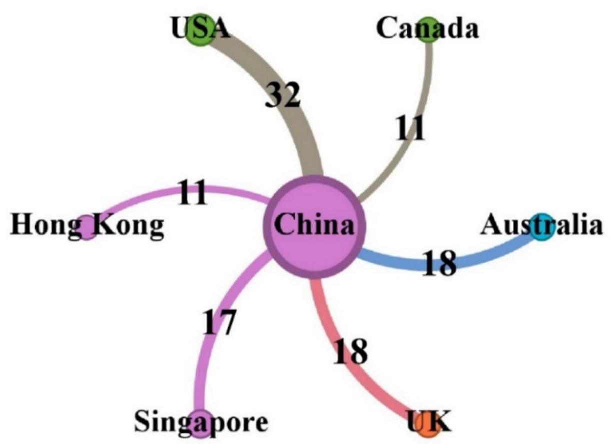


**Fig. 8** Regional collaborations where the frequency ranges from 11 to 32

South Korea and Pakistan; (4) the Czech Republic, the USA, and India; and (5) Vietnam, Japan, Spain, China, Italy, and Macau.

Institutional partnerships are shown in Figs. 11, 12, and 13, with cooperation frequencies ranging from 4 to 21. Four universities' partnerships are shown in Fig. 11, with a range of collaborative frequencies from 12 to 21. China is home to all four of these institutions. Two collaborative clusters, including (1) the University of Chinese Academy of Sciences and the Chinese Academy of Sciences and (2) Shandong Jiaotong University and Shandong Normal University, showcase their strong collaboration. Seven

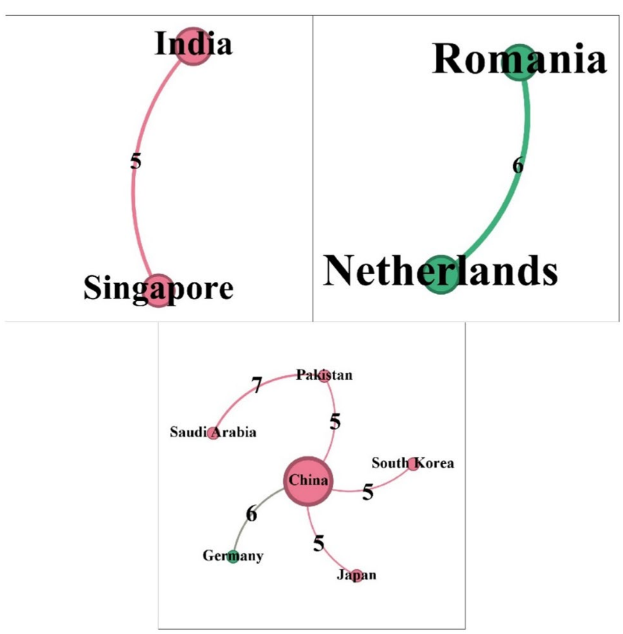


**Fig. 9** Regional collaborations where the frequency ranges from five to seven

university partnerships are shown in Fig. 12, with a range of five to six cooperation frequencies. Three collaborative clusters demonstrate how closely they collaborate: (1) Erasmus University and Bucharest University of Economic Studies; (2) University of Warwick, Peng Cheng Lab, and Harbin Institute of Technology; and (3) Ryerson University and East China Normal University. Six collaborative networks with a collaboration frequency of four, created by 15 universities, are depicted in Fig. 13. Numerous collaborative partners, including (1) Beijing Municipal Commission of Education and Beijing Jiaotong University; (2) Vietnam National University, Ton Duc Thang University, and Electric Power University; (3) East China Normal University and Fudan University; and (4) Ryerson University and York University, demonstrate the substantial cooperation within these seven collaborative networks among organizations from the same nation or area.

The collaborative network visualization shows China's leadership and involvement in collaborating with different countries. According to [89], scientific collaborations, by allowing the sharing of knowledge, experience, technologies, and resources, are regarded as important channels to achieve research visibility and high-quality achievements, as witnessed by the performance of China in the field of DL-ABSA research. The high level of collaboration found in this study can be explained by the interdisciplinary nature of DL-ABSA research [90]. Specifically, in addition to relying primarily on computer science and AI, research on DL-ABSA has benefited from other fields such as psychology, linguistics, neuroscience, and cognitive science [17]. As a result, the study of DL-ABSA is increasingly multidisciplinary. As [91] suggests, the study of complex and multidisciplinary issues brings together researchers from various regions and areas. However, aligning with prior reviews (e.g., [43, 57, 87]), our results show high levels of collaboration in DL-ABSA studies within national borders due mainly to geographic proximity and ease of communication [92].

## Frequently Used Words/Phrases

Table 5 shows the 50 most commonly occurring words. At the top of the list, "opinion," which has been used in 223 articles, is the most often occurring word (25.11%). "Aspect-level" (22.75%), "term" (22.41%), "extraction" (21.51%), "graph" (17.79%), "dependency" (17.45%), "convolutional" (16.78%), "language" (15.77%), and "target" (15.54%) are other important terms. This study also included the non-parametric MK test results with annual term frequency data. The majority of the terms on the list, including "syntactic," "dependency," "opinion," "term," "extraction," "graph," and "convolutional," showed statistically significant increases in frequency.

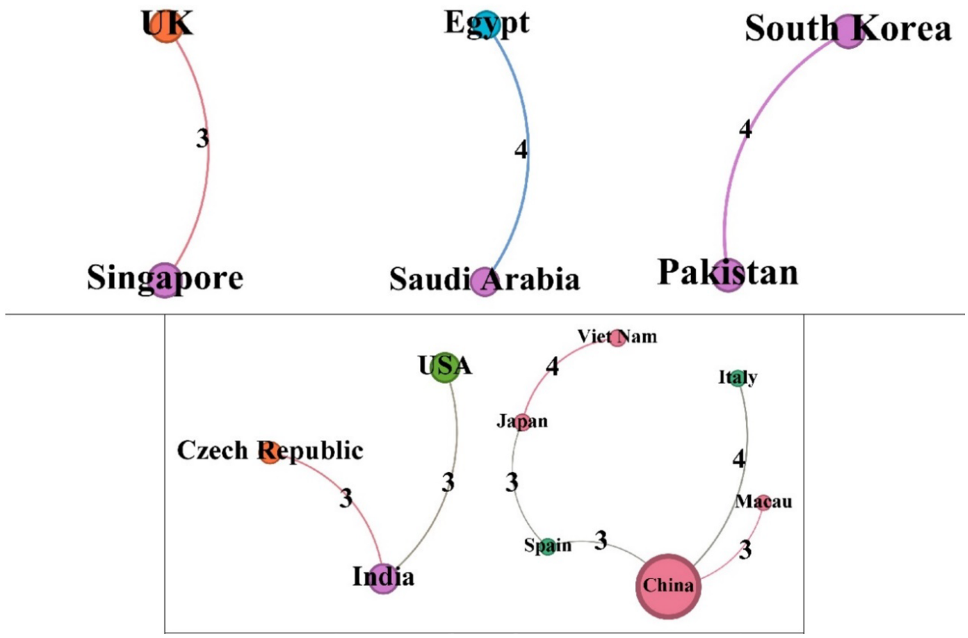


**Fig. 10** Regional collaborations where the frequency ranges from three to four

Table 6 highlights commonly used phrases. Of these, "sentiment polarity" is the most frequently chosen phrase, appearing in 161 articles. Other frequently used terms include "neural network" (153 articles), "aspect term" (94 articles), "convolutional network" (92 articles), "attention mechanism" (91 articles), and "deep learning" (74 articles). The trend test revealed that many phrases showed notable variations in frequency: "sentiment polarity," "aspect term," "convolutional network," and "dependency tree."

The trends in the frequency of terms and phrases observed in the DL-ABSA studies are driven by advances in DL technologies, improvements in data processing, increased interest in fine-grained sentiment analysis, and the growing need for the application of DL-ABSA in real-world scenarios. For example, the increased frequencies of "convolutional" and "convolutional network" reflect the increasing application of CNNs and other neural network models to capture local features in textual data to improve accuracy in identifying aspect-specific emotions [56]. Similarly, the rise in the frequency of "attention mechanism" is driven by the interest in exploiting attention mechanisms and transformer models such as BERT and GPT to improve the ABSA models' abilities to focus on relevant parts of texts [93, 94]. In addition, terms such as "dependency," "syntactic," and "dependency tree" appear with increasing frequency due to the increasing emphasis on the use of syntax and dependency parsing to understand sentence structure to improve the extraction

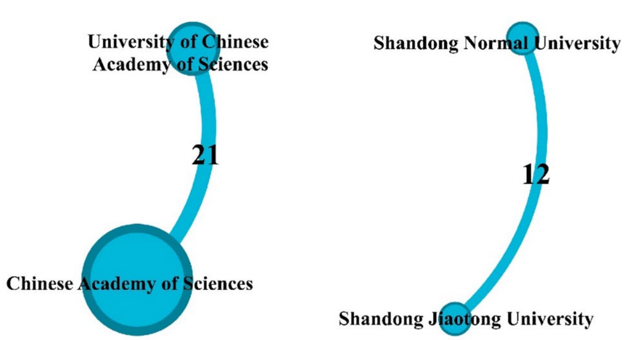


**Fig. 11** Institutional collaborations where the frequency ranges from 12 to 21

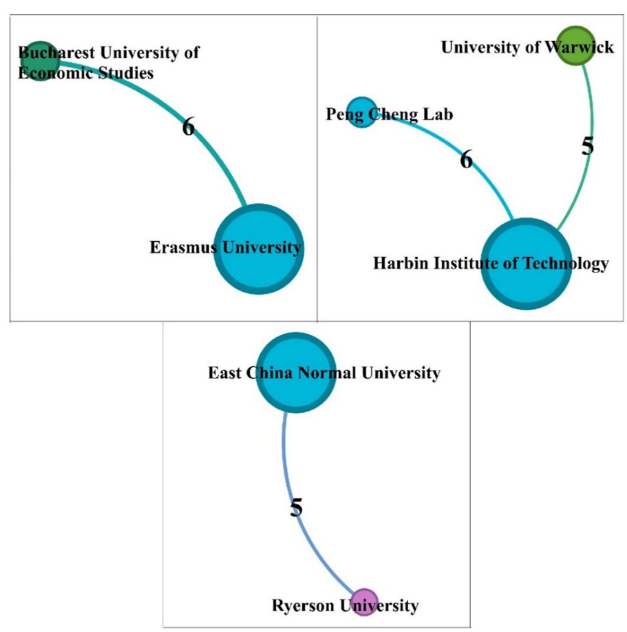


**Fig. 12** Institutional collaborations where the frequency ranges from five to six

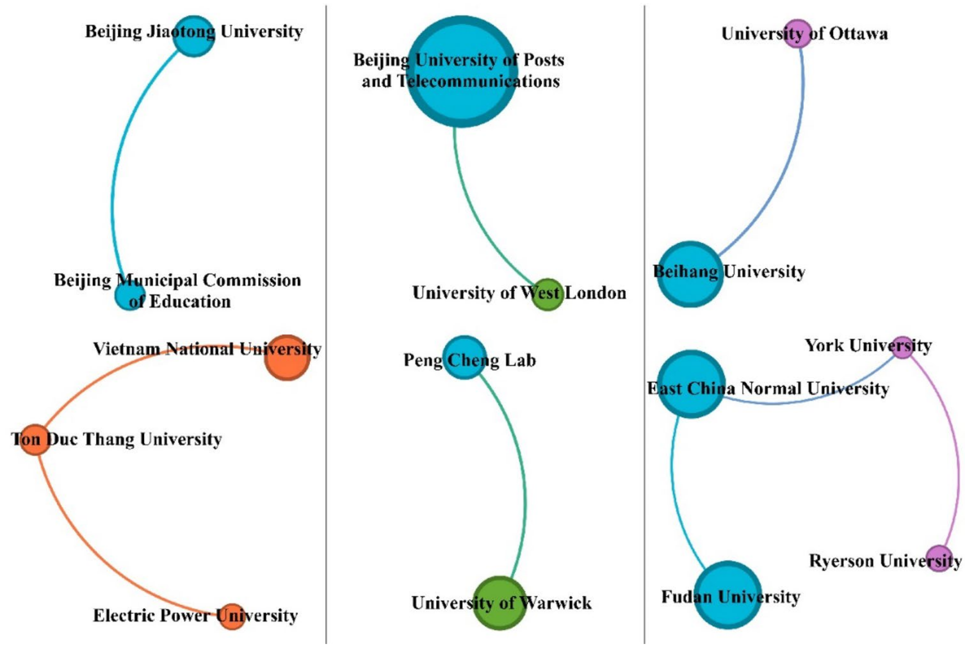


**Fig. 13** Institutional collaborations where the frequency is four

**Table 5** Frequently used words

| Terms | P | PP | MK test | | | Terms | P | PP | MK test | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | $p$ | $S$ | trend | | | | $p$ | $S$ | trend |
| Opinion | 223 | 25.11% | 0.0044 | 24 | ↑↑↑ | Embedding | 78 | 8.67% | 0.0416 | 17 | ↑↑ |
| Aspect-level | 202 | 22.75% | 0.0461 | 17 | ↑↑ | Online | 78 | 8.56% | 0.0170 | 20 | ↑↑ |
| Term | 199 | 22.41% | 0.0020 | 26 | ↑↑↑ | Label | 77 | 8.45% | 0.0028 | 25 | ↑↑↑ |
| Extraction | 191 | 21.51% | 0.0044 | 24 | ↑↑↑ | Training | 77 | 8.11% | 0.0020 | 26 | ↑↑↑ |
| Graph | 158 | 17.79% | 0.0028 | 25 | ↑↑↑ | Interaction | 76 | 7.77% | 0.0028 | 25 | ↑↑↑ |
| Dependency | 155 | 17.45% | 0.0008 | 28 | ↑↑↑↑ | Score | 75 | 7.43% | 0.0187 | 20 | ↑↑ |
| Convolutional | 149 | 16.78% | 0.0012 | 27 | ↑↑↑ | Prediction | 72 | 7.32% | 0.0017 | 26 | ↑↑↑ |
| Language | 140 | 15.77% | 0.0461 | 17 | ↑↑ | Improvement | 69 | 7.32% | 0.0044 | 24 | ↑↑↑ |
| Target | 138 | 15.54% | 0.1346 | 13 | ↑ | Vector | 66 | 7.32% | 0.0635 | 16 | ↑ |
| Knowledge | 119 | 13.40% | 0.0053 | 23 | ↑↑↑ | Category | 65 | 7.21% | 0.0248 | 19 | ↑↑ |
| Syntactic | 116 | 13.06% | 0.0012 | 27 | ↑↑↑ | Sequence | 65 | 7.21% | 0.0170 | 20 | ↑↑ |
| Framework | 113 | 12.73% | 0.0028 | 25 | ↑↑↑ | Technique | 65 | 7.09% | 0.0170 | 20 | ↑↑ |
| Enhance | 111 | 12.50% | 0.0028 | 25 | ↑↑↑ | Contextual | 64 | 7.09% | 0.0291 | 18 | ↑↑ |
| Domain | 109 | 12.27% | 0.0094 | 22 | ↑↑↑ | Train | 64 | 6.87% | 0.0327 | 18 | ↑↑ |
| Level | 105 | 11.82% | 0.1346 | 13 | ↑ | Detection | 63 | 6.87% | 0.0061 | 23 | ↑↑↑ |
| Structure | 97 | 10.92% | 0.0028 | 25 | ↑↑↑ | Set | 63 | 6.87% | 0.0248 | 19 | ↑↑ |
| User | 94 | 10.59% | 0.0127 | 21 | ↑↑ | Pre-trained | 61 | 6.87% | 0.0070 | 22 | ↑↑↑ |
| Absa | 93 | 10.47% | 0.0028 | 25 | ↑↑↑ | Significantly | 61 | 6.87% | 0.0031 | 24 | ↑↑↑ |
| Bert | 90 | 10.14% | 0.0109 | 21 | ↑↑ | Subtask | 61 | 6.76% | 0.0039 | 24 | ↑↑↑ |
| Memory | 85 | 9.57% | 0.3688 | 8 | ↑ | Tree | 61 | 6.76% | 0.0012 | 27 | ↑↑↑ |
| Product | 85 | 9.57% | 0.0039 | 24 | ↑↑↑ | Twitter | 61 | 6.64% | 0.0083 | 22 | ↑↑↑ |
| Relation | 84 | 9.46% | 0.0094 | 22 | ↑↑↑ | Mining | 60 | 6.42% | 0.1024 | 14 | ↑ |
| Social | 84 | 9.46% | 0.0028 | 25 | ↑↑↑ | Service | 60 | 8.67% | 0.0061 | 23 | ↑↑↑ |
| System | 82 | 9.23% | 0.0355 | 18 | ↑↑ | Embed | 59 | 8.56% | 0.2581 | 10 | ↑ |
| Layer | 79 | 8.90% | 0.0028 | 25 | ↑↑↑ | Global | 57 | 8.45% | 0.0327 | 18 | ↑↑ |

Similar to Table 4. Ascending (descending) trend but not statistically significant ($p > 0.05$); statistically growing (decreasing) for ↑↑(↓↓), ↑↑↑(↓↓↓), and ↑↑↑↑(↓↓↓↓) ($p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively). S: MK test statistics

**Table 6** Frequently used phrases

| Phrases | P | PP | MK test | | |
|---|---|---|---|---|---|
| | | | $p$ | S | trend |
| Sentiment polarity | 161 | 18.13% | 0.00277 | 25 | ↑↑↑ |
| Neural network | 153 | 13.46% | 0.1346 | 13 | ↑ |
| Aspect term | 94 | 10.59% | 0.009375 | 22 | ↑↑↑ |
| Convolutional network | 92 | 10.36% | 0.001189 | 27 | ↑↑↑ |
| Attention mechanism | 91 | 10.25% | 0.04606 | 17 | ↑↑ |
| Deep learning | 74 | 8.33% | 0.0113 | 21 | ↑↑ |
| Semantic information | 44 | 4.95% | 0.008321 | 22 | ↑↑↑ |
| Sentiment classification | 65 | 7.32% | 0.07619 | 15 | ↑ |
| Natural language processing | 41 | 4.62% | 0.05945 | 16 | ↑ |
| Aspect term extraction | 40 | 4.50% | 0.001681 | 26 | ↑↑↑ |
| Aspect category | 33 | 3.72% | 0.0809 | 15 | ↑ |
| Aspect word | 33 | 3.72% | 0.01471 | 20 | ↑ |
| Syntactic information | 32 | 3.60% | 0.00962 | 21 | ↑↑↑ |
| Aspect extraction | 31 | 3.49% | 0.1669 | 12 | ↑ |
| Dependency tree | 31 | 3.49% | 0.003851 | 24 | ↑↑↑ |
| Opinion word | 30 | 3.38% | 0.01265 | 21 | ↑↑ |
| Context word | 28 | 3.15% | 0.05945 | 16 | ↑ |
| Online review | 28 | 3.15% | 0.03267 | 18 | ↑↑ |
| Opinion mining | 28 | 3.15% | 0.1669 | 12 | ↑ |
| Social medium | 26 | 2.93% | 0.008321 | 22 | ↑↑↑ |
| Syntactic structure | 23 | 2.59% | 0.01342 | 19 | ↑↑ |
| Multiple aspect | 19 | 2.14% | 0.1285 | 13 | ↑ |
| Neural model | 19 | 2.14% | 0.1024 | 14 | ↑ |
| Short-term memory | 19 | 2.14% | 0.02907 | 18 | ↑↑ |
| Aspect information | 18 | 2.03% | 1 | 1 | ↑ |
| Opinion term | 18 | 2.03% | 0.09511 | 14 | ↑ |
| Pre-trained language model | 17 | 1.91% | 0.05447 | 15 | ↑ |
| User review | 16 | 1.80% | 0.0113 | 21 | ↑↑ |
| Aspect category detection | 15 | 1.69% | 0.00962 | 21 | ↑↑↑ |
| Opinion target | 15 | 1.69% | 0.6124 | 5 | ↑ |
| Restaurant datasets | 15 | 1.69% | 0.7957 | 3 | ↑ |
| Twitter datasets | 15 | 1.69% | 0.03833 | 17 | ↑↑ |
| External knowledge | 14 | 1.58% | 0.00583 | 22 | ↑↑↑ |
| Sentiment word | 14 | 1.58% | 0.05413 | 16 | ↑ |
| Syntactic dependency | 14 | 1.58% | 0.00734 | 21 | ↑↑↑ |
| Dependency relation | 13 | 1.46% | 0.02907 | 18 | ↑↑ |
| Graph attention network | 13 | 1.46% | 0.0044 | 23 | ↑↑↑ |
| Multi-head attention | 24 | 2.70% | 0.02393 | 18 | ↑↑ |
| Semantic relationship | 13 | 1.46% | 0.05413 | 16 | ↑ |
| Semantic representation | 13 | 1.46% | 0.04888 | 16 | ↑↑ |
| Adversarial training | 12 | 1.35% | 0.01584 | 19 | ↑↑ |
| Local context | 12 | 1.35% | 0.0126 | 20 | ↑↑ |
| Multi-task learning | 12 | 1.35% | 0.05413 | 16 | ↑ |
| Social network | 12 | 1.35% | 0.02907 | 18 | ↑↑ |
| Aspect representation | 11 | 1.24% | 0.08783 | 14 | ↑ |
| Contextual word | 11 | 1.24% | 0.197 | 10 | ↑ |
| Dependency graph | 11 | 1.24% | 0.03199 | 17 | ↑↑ |
| Semantic feature | 11 | 1.24% | 0.08219 | 13 | ↑ |
| Sentiment feature | 11 | 1.24% | 0.2836 | 9 | ↑ |
| Short-term memory network | 11 | 1.24% | 1 | −1 | ↓ |

Similar to Table 5

accuracy of terms and their associated emotions [21, 95]. Similarly, the use of graph-based methods to represent dependencies and relationships between words has gained attention, as witnessed by the term "graph," to capture complex dependencies and improve ABSA performance [96, 97].

## Topic and Trend Analysis

Figure 14 shows the results of the topic modeling, including article proportions and suggested labels. The top four topics with the most frequency included "syntax and structure analysis for sentiment analysis" (9.30%), "neural networks for sequence modeling and sentiment analysis" (8.62%), "specific aspects and modalities in sentiment analysis" (8.20%), and "ABSA for multi-task learning" (8.18%).

Topics related to grammar and structure, neural networks, specific aspects, and multi-task learning highlight the importance of applying both basic and advanced technologies to improve ABSA performance. Specifically, the use of dependency resolution, syntax trees, and other structural analysis methods is helpful for understanding the syntactic and structural aspects of language and capturing the relationships between words and their contextual meanings [98, 99], thus improving accuracy in extracting aspects and their associated emotions [100]. Second, neural networks such as RNNs, LSTMs, and transformers are regarded as important in text sequence data modeling due to their abilities to capture remote dependencies and contextual information in ABSA [101]. Furthermore, the combination of specific aspects (e.g., product features) and patterns (e.g., text, images, or multimodal data) allows for detailed and nuanced analysis of emotions, especially in real-world applications with different aspects or types of data [102, 103]. In addition, multi-task learning, which involves simultaneous model training on multiple relevant tasks, has been increasingly exploited to improve ABSA performance by leveraging shared information across tasks, such as aspect extraction and sentiment classification [104].

The trend analysis for the 15 topics is shown in Fig. 15, which displays the 15 topics' respective dynamic prevalence over time throughout the whole dataset. For example, topics such as "syntax and structure analysis for sentiment analysis," "categorization and identification for ABSA,"

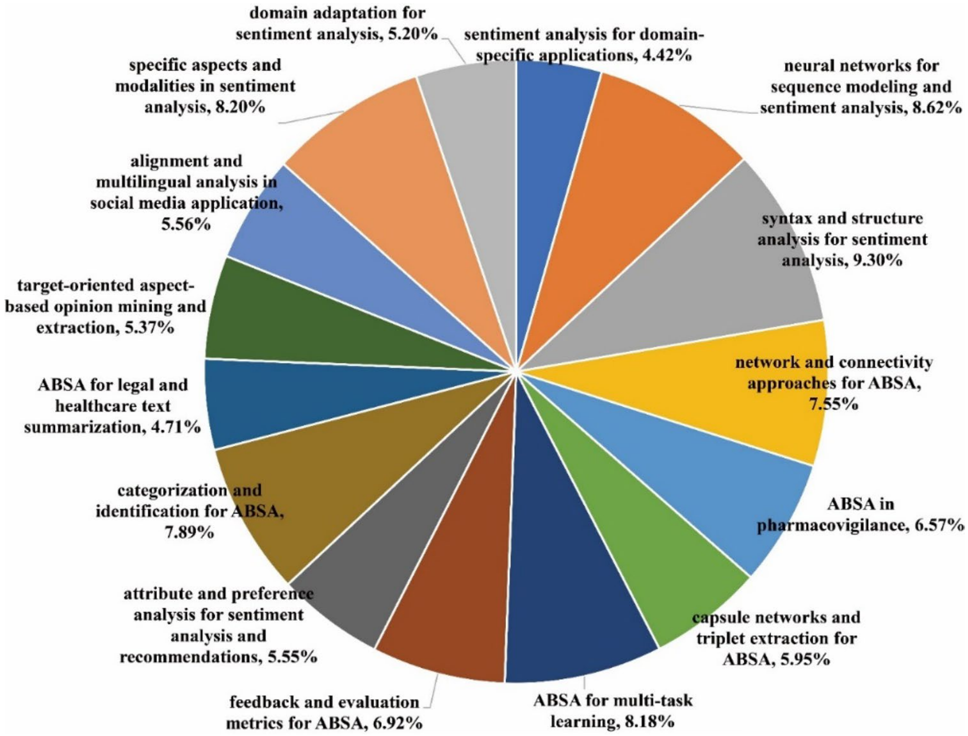


**Fig. 14** Topic proportions and labels

"domain adaptation for sentiment analysis," "network and connectivity approaches for ABSA," and "ABSA in pharmacovigilance" have shown a constant increase over the studied period. Other topics, such as "sentiment analysis for domain-specific applications" and "target-oriented aspect-based opinion mining and extraction," have shown a constant decrease over the studied period. Topics such as "specific aspects and modalities in sentiment analysis" and "alignment and multilingual analysis in social media application" have shown a decrease in the last 3 years.

The evolution of research topics shows the ongoing innovation and expanding application of DL-ABSA in various domains. Specifically, the need for more accurate and sophisticated models to understand language structure has ensured constant attention has been paid to syntax and structure analysis in DL-ABSA research [105]. Second, as foundational tasks in ABSA, categorizing and identifying aspects and sentiments have been improved in terms of accuracy alongside the advances in DL technologies [9, 106]. Third, the increased research interest in domain adaptation for ABSA is attributed to the need for transferring models across various domains (e.g., from product reviews to restaurant reviews) without decreasing model performance [107–109]. Furthermore, attention has also been paid to exploring graph neural networks to represent and utilize connectivity in textual data by leveraging the relationships between entities and words [110]. In addition, the growing interest in monitoring and analyzing drug safety and adverse effects has driven ongoing research in applying DL-ABSA models in pharmacovigilance [111].

The interrelations among the 15 topics revealed the presence of four separate groupings (Fig. 16). Group 1 (G1) encompassed "attribute and preference analysis for sentiment analysis and recommendations" and "feedback and evaluation metrics for ABSA." Group 2 (G2) included three topics: "ABSA for multi-task learning," "capsule networks and triplet extraction for ABSA," and "target-oriented aspect-based opinion mining and extraction." Group 3 (G3) included two topics: "neural networks for sequence modeling and sentiment analysis" and "specific aspects and modalities in sentiment analysis." Group 4 (G4) comprised two topics: "syntax and structure analysis for sentiment analysis" and "network and connectivity approaches for ABSA."

The interrelations among topics show how different research areas interact with each other. Specifically, topics in G1 highlight the increasing need for understanding user preferences based on user feedback analysis and evaluating the effectiveness of ABSA systems [112, 113]. Second, topics in G2 show an increasing focus on the application of cutting-edge methods such as multi-task learning and capsule networks in target-oriented mining for precise ABSA [13, 114]. Furthermore, G3 suggests a rise in the use of neural networks for modeling sequences and focusing on specific aspects or modalities for capturing detailed and contextual sentimental information [115]. In addition, topics in G4 demonstrate an increased trend in capturing dependencies and connections to understanding the structural relationships within textual data to improve sentiment and aspect extraction [21].

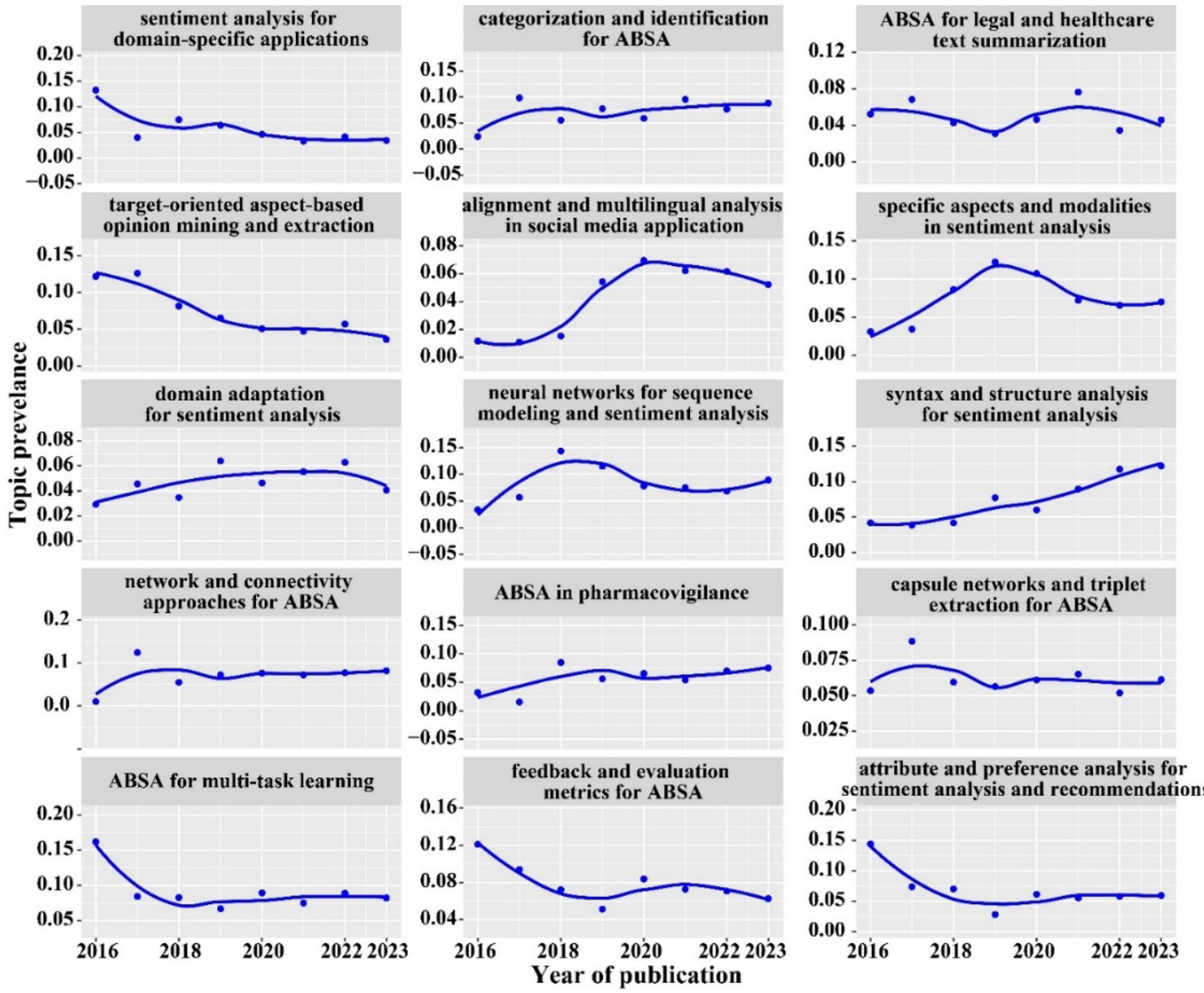


**Fig. 15** Trends of the 15 topics

## Research Hotspots and Trends

"Frequently Used Words/Phrases" and "Topic and Trend Analysis" have revealed that research methodologies and issues within DL-ABSA demonstrate continuous evolution. Research on DL-ABSA has experienced a notable surge in activity, with several distinct hotspots and trends emerging from the analysis of scholarly literature.

### Topics with High Frequency

First, "syntax and structure analysis for sentiment analysis" has emerged as a prominent hotspot, capturing 9.30% of the research focus, reflecting the recognition of the pivotal role played by syntactic and structural features in capturing nuanced sentiment expressions [116]. By leveraging syntactic information, researchers can enhance the depth and granularity of sentiment analysis, allowing for more accurate identification and interpretation of sentiment-bearing elements within textual data [117]. The focus on syntax underscores a strategic effort to harness linguistic insights and computational methods to overcome challenges related to ambiguity and context dependency inherent in sentiment analysis tasks [118].

Second, "neural networks for sequence modeling and sentiment analysis" has garnered significant attention, representing 8.62% of the research focus. This underscores the growing reliance on DL techniques to model sequential data and extract meaningful patterns from textual contexts. Neural networks offer unparalleled capabilities in learning complex representations, enabling ABSA models to discern subtle sentiment

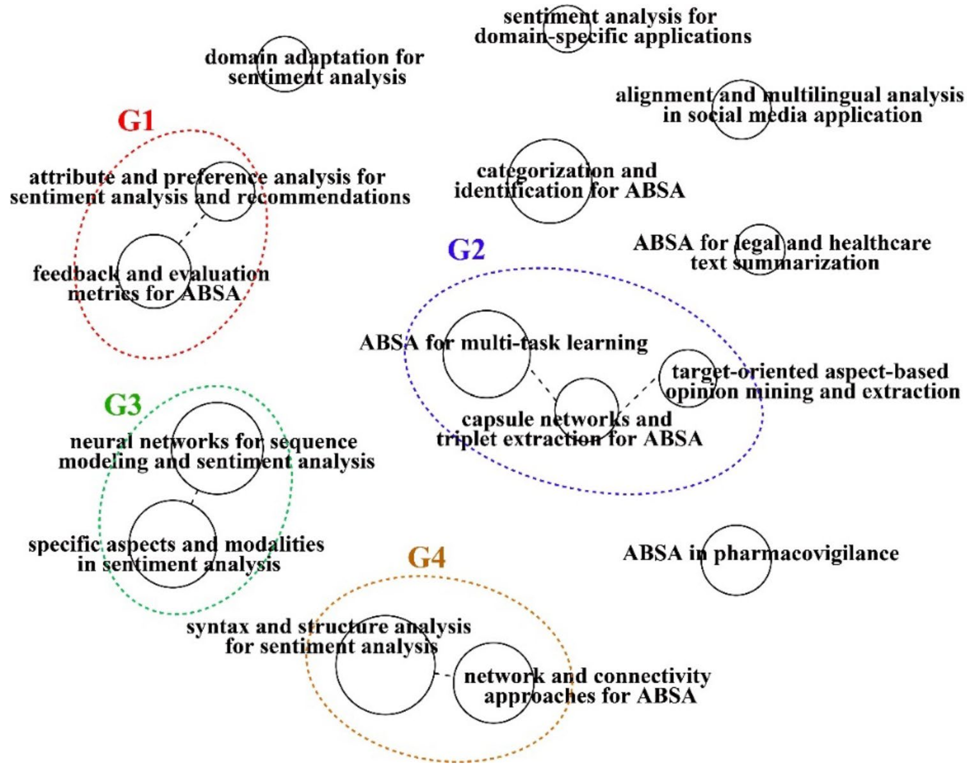


**Fig. 16** Topic correlation visualization

nuances across diverse domains and textual modalities [119]. The widespread adoption of neural architectures reflects their scalability, adaptability, and effectiveness in capturing contextual dependencies [12], thereby driving advancements in ABSA research and facilitating the development of more robust and versatile sentiment analysis solutions.

Third, the exploration of “specific aspects and modalities in sentiment analysis” has emerged as a critical hotspot, comprising 8.20% of the research focus, reflecting the emphasis on the identification and analysis of specific attributes, domains, or modalities that influence sentiment orientations [120]. By dissecting sentiment at a finer granularity, researchers can uncover domain-specific patterns, linguistic markers, and contextual nuances, enabling targeted and contextually informed ABSA solutions. The emphasis on specificity underscores a maturing understanding of sentiment dynamics and the need for tailored approaches to accommodate diverse application scenarios and user preferences [121].

Fourth, “ABSA for multi-task learning” has emerged as a notable trend, capturing 8.18% of the research focus. This signifies a strategic shift toward more holistic and integrated ABSA frameworks capable of addressing multiple related tasks simultaneously [122, 123]. Multi-task learning approaches offer synergistic benefits, including improved generalization, enhanced model robustness, and efficient knowledge transfer across tasks [124]. The growing interest in multi-task learning demonstrates a concerted effort to develop comprehensive ABSA solutions capable of capturing the multifaceted nature of sentiment analysis tasks and accommodating the diverse needs of real-world applications [125].

## Topics Receiving Increasing Attention

The trend analysis of topics in DL-ABSA reveals several persistent hotspots and emerging trends that are shaping the landscape of research in this field. Notably, topics such as “categorization and identification for ABSA,” “domain adaptation for sentiment analysis,” “network and connectivity approaches for ABSA,” and “ABSA in pharmacovigilance” have shown a constant increase in prevalence over the studied period, indicating their significance as research hotspots.

First, the consistent rise in attention toward “categorization and identification for ABSA” underscores the ongoing efforts to develop robust methodologies for accurately categorizing and identifying sentiment-bearing aspects within textual data [126]. As ABSA becomes increasingly integral to applications such as recommendation systems, market analysis, and social media monitoring, the need for effective categorization and identification techniques has intensified [127]. DL approaches offer promising solutions by leveraging rich representations and contextual information to discern subtle sentiment nuances across diverse domains and textual modalities.

Second, “domain adaptation for sentiment analysis” has become a well-known hotspot, reflecting the growing recognition of the difficulties brought about by domain shifts in ABSA tasks. With sentiment expression varying significantly across different domains and contexts, domain adaptation methods are essential for improving the generalization and robustness of ABSA models [13]. By leveraging transfer learning and domain-specific knowledge, researchers aim to develop adaptive ABSA solutions capable of effectively handling domain shifts and accommodating the diverse needs of real-world applications [128, 129].

Furthermore, the increasing emphasis on “network and connectivity approaches for ABSA” signifies a strategic focus on leveraging network science principles and graph-based representations to capture complex relationships and dependencies among sentiment-bearing elements [58]. By modeling the interconnectedness of aspects, sentiments, and contextual information, network-based approaches offer insights into the underlying structures and dynamics of sentiment analysis tasks, enabling more accurate and interpretable ABSA solutions [130].

Lastly, the growing interest in “ABSA in pharmacovigilance” highlights the critical role of sentiment analysis in pharmacovigilance efforts aimed at monitoring adverse drug reactions and ensuring public health safety [131]. The amount of textual data relevant to pharmacovigilance has increased due to the growth of social media platforms, Internet forums, and healthcare databases, necessitating advanced ABSA techniques for efficient and timely detection of adverse events [125, 132]. Utilizing DL techniques in pharmacovigilance enables automated analysis of large-scale textual data, facilitating early detection and intervention in adverse drug events, thereby enhancing patient safety and regulatory compliance [133].

## Groups Among Topics

The identification of distinct groupings among topics in DL-ABSA sheds light on key research hotspots and emerging trends in the field. First, G1, encompassing “attribute and preference analysis for sentiment analysis and recommendations” alongside “feedback and evaluation metrics for ABSA,” underscores the importance of fine-grained attribute analysis and robust evaluation methodologies in ABSA research. This group reflects the ongoing efforts to develop more sophisticated ABSA models capable of capturing nuanced aspects of sentiment expression and providing actionable insights for recommendation systems [134]. The emphasis on attribute analysis and evaluation metrics highlights a strategic focus on improving the interpretability, accuracy, and utility of ABSA solutions, thereby addressing critical challenges in real-world deployment scenarios [135, 136].

Second, G2, comprising “ABSA for multi-task learning,” “capsule networks and triplet extraction for ABSA,” and “target-oriented aspect-based opinion mining and extraction,” represents a convergence of innovative methodologies aimed at advancing ABSA. The inclusion of multi-task learning underscores a growing interest in holistic ABSA frameworks capable of simultaneously addressing multiple related tasks, enhancing model efficiency, and generalization [36]. Additionally, the integration of capsule networks and triplet extraction techniques reflects a shift toward more specialized and context-aware ABSA models capable of capturing complex relationships and dependencies among sentiment-bearing elements [13]. The focus on target-oriented aspect-based opinion mining underscores the importance of contextually informed sentiment analysis, tailored to specific domains or user preferences, thus driving advancements in personalized recommendation systems and opinion summarization [137].

G3, consisting of “neural networks for sequence modeling and sentiment analysis” and “specific aspects and modalities in sentiment analysis,” highlights the foundational role of DL techniques in ABSA research and the ongoing exploration of domain-specific sentiment dynamics [138]. The utilization of neural networks for sequence modeling underscores their efficacy in capturing temporal dependencies and contextual nuances in textual data, facilitating more accurate sentiment analysis outcomes across diverse domains. Furthermore, the emphasis on specific aspects and modalities reflects a nuanced approach toward sentiment analysis, aimed at identifying and analyzing domain-specific patterns, linguistic markers, and contextual nuances that influence sentiment orientations, thereby addressing the diverse needs of real-world ABSA applications [139, 140].

G4, comprising “syntax and structure analysis for sentiment analysis” and “network and connectivity approaches for ABSA,” highlights the intersection of linguistic insights and computational methodologies in ABSA research [141]. The focus on syntax and structural analysis underscores the importance of linguistic features in capturing nuanced sentiment expressions, enhancing the interpretability and accuracy of ABSA models [142]. Similarly, the exploration of network and connectivity approaches reflects efforts to leverage network science principles and graph-based representations for capturing complex relationships and dependencies among sentiment-bearing elements, thereby advancing ABSA [143].

In summary, the identified hotspots and trends in DL-ABSA reflect research priorities aimed at addressing key challenges, advancing state-of-the-art methodologies, and fostering the creation of effective and adaptable sentiment analysis solutions tailored to diverse application domains. These hotspots underscore the interdisciplinary nature of ABSA research, bridging linguistic insights, computational methods, and domain-specific knowledge to propel the field forward and address the evolving needs of sentiment analysis in various domains. By addressing these hotspots through innovative methodologies and interdisciplinary collaborations, researchers can drive advancements in DL-ABSA research, leading to the creation of accurate, adaptable, and contextually aware sentiment analysis solutions tailored to diverse application domains and user preferences.

## Conclusion and Implications

### Conclusion

The comprehensive bibliometric and topic modeling analysis conducted on DL-ABSA research revealed several key insights and trends. First, there has been a significant increase in both the volume and impact of research in this field, with a significant increase in citations and publications starting in 2020. This underscores the growing importance and impact of DL-ABSA research within the academic community.

Second, the analysis identified prominent publication sources, research areas, institutions, and countries/regions contributing to DL-ABSA research. Journals such as IEEE Access and conferences such as the AAAI Conference on Artificial Intelligence emerged as significant publication venues, while institutions from China, particularly the Chinese Academy of Sciences, demonstrated a substantial presence in DL-ABSA research. Additionally, collaborative efforts between countries/regions, particularly between the USA and China, were observed, highlighting the global engagement and cooperation in advancing DL-ABSA research.

Third, the analysis of major themes and topics in DL-ABSA research revealed key areas of focus, such as syntax and structure analysis, neural networks for sequence modeling, and specific aspects and modalities in sentiment analysis. These topics reflect the diverse research landscape and the ongoing exploration of innovative methodologies and approaches to enhance DL-ABSA techniques.

Finally, the identification of distinct groupings among DL-ABSA topics provided valuable insights into the interrelations and thematic clusters within the field. These groupings, such as attribute and preference analysis, multi-task learning, and network and connectivity approaches, offer guidance for researchers to explore interdisciplinary collaborations and advance DL-ABSA research in strategic directions.

In conclusion, this research provides an extensive summary of the publication trends, collaborative networks, thematic clusters, and emerging directions in DL-ABSA research. By leveraging these insights, researchers can identify research gaps, foster collaborations, and drive advancements in DL-ABSA methodologies, ultimately contributing to developing accurate, interpretable, and contextually aware sentiment analysis solutions tailored to diverse application domains.

However, this study has its limitations. First, it only used the WoS database. Although the WoS is popularly used in literature reviews, there might still be DL-ABSA publications that were not included in our analysis. Future work might consider including data from more databases. Second, this study did not analyze specific elements of a publication, such as what systematic reviews do. Future work could exploit ways to effectively integrate the advantages of text mining and systematic analysis to promote an in-depth understanding of specific aspects of DL-ABSA literature.

### Implications for Practice and Prospective Avenues in ABSA Research

The evolving landscape of DL-ABSA research unveils multifaceted implications for both practice and prospective avenues. The prominence of "syntax and structure analysis for sentiment analysis" signals a strategic emphasis on leveraging linguistic insights to enhance sentiment analysis accuracy. Integrating syntactic features into DL-ABSA models holds promise for practitioners, enabling them to capture nuanced sentiment expressions and address challenges related to ambiguity and context dependency. Moreover, the surge in attention toward "neural networks for sequence modeling and sentiment analysis" underscores the pivotal role of DL in ABSA research, offering practitioners scalable and adaptable solutions to discern subtle sentiment nuances across diverse textual data sources. This trend suggests prospective avenues for practitioners to explore novel neural architectures tailored to ABSA tasks, fostering more effective sentiment analysis outcomes.

Furthermore, the exploration of "specific aspects and modalities in sentiment analysis" signifies a shift toward contextually informed ABSA solutions tailored to diverse application domains and user preferences. Practitioners can leverage this trend to focus on identifying domain-specific patterns and linguistic markers, thereby enhancing the relevance and applicability of ABSA models. Additionally, the rising interest in "ABSA for multi-task learning" offers opportunities for practitioners to develop comprehensive frameworks capable of addressing multiple related tasks simultaneously, thus improving model efficiency and adaptability.

The identified hotspots also shed light on prospective avenues for practitioners in specific domains. For instance, the emphasis on "domain adaptation for sentiment analysis" underscores the importance of developing adaptive DL-ABSA solutions capable of handling domain shifts, which is particularly relevant for practitioners operating in diverse contexts. Moreover, the growing attention toward "ABSA in pharmacovigilance" presents practitioners in the healthcare domain with opportunities to leverage DL methods for efficient and timely detection of adverse drug events, thereby enhancing patient safety and regulatory compliance.

In summary, the integration of diverse research hotspots and trends in DL-ABSA research underscores the interdisciplinary nature of the field and offers practitioners a roadmap for advancing sentiment analysis methodologies and applications. By leveraging linguistic insights, computational methods, and domain-specific knowledge, practitioners can drive innovations in DL-ABSA research, leading to accurate, adaptable, and contextually aware DL-ABSA solutions tailored to diverse application domains and user preferences.

## Appendix

**Table 7** Search query

| |
|---|
| ((TS = ((("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 = (("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 = (("facial" or "speech" or "sound*" or "face" or "dance" or "temperature" or "image*" or "spoken" or "electroencephalography" or "EEG" or "biosignal*" or "voice*")) |

**Table 8** Exclusion criteria related to ABSA

| |
|---|
| (1) Detection and classification of physical emotions and medical conditions |
| (2) Recognition of affective postures |
| (3) Research focused on the analysis and identification of emotions through various mediums such as photos, human facial expressions, physiology, and electrical signals like electrocardiograms |
| (4) Investigation into humans' ability for emotion recognition |
| (5) Exploration of theory of mind |
| (6) Psychological or pharmacological experimental studies |
| (7) Creation of ontologies, corpora, or datasets |
| (8) Literature reviews or survey papers |
| (9) Multimodal analysis as opposed to solely text analysis |

**Table 9** Research issues, technologies used, purpose, and effectiveness of technology used in the top 25 DL-ABSA studies

| Studies | Research issue | Technologies used | Purpose of technology used | Effectiveness | TCS | MCS |
|---|---|---|---|---|---|---|
| [58] | Determine the sentiment polarity | GCN | To extract graph representations | Effective in enhancing word dependencies in sentences and improving sentiment extraction learning ability. Effective in constructing un-directional graphs to fully utilize sentence dependency trees and derive precise affective relations | 164 | 82 |
| | | SenticNet | To leverage affective dependencies for specific aspects | | | |
| | | Dependency tree | To capture syntactical information | | | |
| | | Aspect-specific affective enhanced dependency graph | To enhance affective information | | | |
| | | LSTM | To derive hidden contextual representations from sentence embeddings | | | |
| | | GloVe | For word embeddings in non-BERT models, capturing semantic relationships | | | |
| | | L2 regularization | To prevent overfitting by penalizing large weights | | | |
| | | Adam optimizer | For efficient parameter optimization | | | |
| | | Uniform initialization | To initialize weights and biases uniformly for neural network layers | | | |
| | | BERT | For contextual word embeddings for sentiment analysis | | | |
| [59] | Hotel recommendation system based on sentiment analysis of the reviews | BERT | To classify sentiments in reviews using an ensemble model with three phases | Effective in reducing computational time and achieving higher accuracy for sentiment analysis by combining all feature settings | 70 | 23.33 |
| | | Word2vec | To generate word vectors as textual features for the sentiment classification model | | | |
| | | TF–IDF | To calculate the importance of frequent words in the reviews as textual features for the classification model | | | |
| | | Random forest classifier | To classify the sentiment of reviews based on various textual features | | | |
| | | Fuzzy logic | To categorize reviews into different aspects by handling misspellings and typographical errors | | | |
| | | TPU v3-8 | To accelerate the training process of the BERT model | | | |
| | | Fuzzy string matching | To improve the accuracy of aspect-based review categorization by handling variations in text | | | |

**Table 9** (continued)

| Studies | Research issue | Technologies used | Purpose of technology used | Effectiveness | TCS | MCS |
|---|---|---|---|---|---|---|
| [81] | Aspect-level sentiment classification | Interactive multitask learning networks | Solves multiple tasks simultaneously, enabling better exploitation of interactions between tasks | Effective in co-extracting aspect and opinion terms. Effective in utilizing domain-specific knowledge through joint training and domain-specific embeddings to enhance task performance. Effective in maintaining competitive performance even without domain-specific embedding | 112 | 22.4 |
| | | Message passing mechanism | Allows informative interactions between tasks by sending useful information back to a shared latent representation | | | |
| | | CNN | Used in the feature extraction component after the word embedding layer to extract features from the input sequence | | | |
| | | Shared latent representation | A sequence of latent vectors shared among all tasks, initialized by the feature extraction component and updated through message passing | | | |
| | | Glove | Provides pre-trained word vectors to capture general semantic information | | | |
| | | FastText | Provides pre-trained word vectors, trained on a large domain-specific corpus for the restaurant and laptop domains | | | |
| | | Adam optimizer | To optimize the learning process | | | |

**Table 9** (continued)

| Studies | Research issue | Technologies used | Purpose of technology used | Effectiveness | TCS | MCS |
|---|---|---|---|---|---|---|
| [76] | Aspect extraction | Neural word embeddings | To map words that usually co-occur within the same context to nearby points in the embedding space | Effective in extracting coherent aspects and identifying separable aspects despite challenges in specific categories such as taste and smell | 220 | 31.43 |
| | | Aspect embeddings | To represent aspects in the same embedding space as words | | | |
| | | Grid search | To optimize hyperparameters of topic models using the topic coherence metric | | | |
| | | Gibbs sampling | To perform 1000 iterations of sampling for all topic models to infer topic distributions | | | |
| | | GibbsLDA++ | To implement LocLDA for topic modeling using Gibbs sampling | | | |
| | | Word2vec | To initialize the word embedding matrix with pre-trained word vectors and set specific parameters | | | |
| | | K-means clustering | To initialize the aspect embedding matrix with cluster centroids from word embeddings | | | |
| | | Adam optimizer | To optimize model parameters during training | | | |
| | | Orthogonality penalty | To enforce an orthogonality constraint on aspect embeddings | | | |
| [71] | Aspect-category sentiment analysis and aspect-term sentiment analysis | CNN | To efficiently extract N-gram features at multiple granularities | Effective in controlling sentiment information flow at a fine granularity. Effective in unraveling aspect and sentiment information. Effective in differentiating the sentiments of multiple entities within the same sentence | 300 | 50 |
| | | Gated Tanh-ReLU units | To selectively output sentiment features based on the given aspect or entity | | | |
| | | Multiple filters in convolutional layers | To capture features at different granularities within each receptive field | | | |
| | | GloVe | To initialize word embedding vectors | | | |
| | | Uniform distribution | To initialize out-of-vocabulary words with a uniform distribution | | | |
| | | Adagrad optimizer | To optimize model parameters | | | |

**Table 9** (continued)

| Studies | Research issue | Technologies used | Purpose of technology used | Effectiveness | TCS | MCS |
|---|---|---|---|---|---|---|
| [77] | Aspect-level sentiment classification | LSTM | To model aspects and texts simultaneously and learn long-term dependencies while avoiding the gradient vanishing or exploding problem | Effective in learning sentiment polarities of different aspects. Effective in identifying sentiment-indicating words for specific aspects when multiple aspects within a sentence | 192 | 32 |
| | | Bi-LSTM | To learn the hidden semantics of words in both the sentence and the aspect target by processing the sequence in both forward and backward directions | | | |
| | | Attention-over-attention module | To automatically generate mutual attention from aspect-to-text and text-to-aspect | | | |
| | | Uniform initialization | To initialize all weight matrices randomly from a uniform distribution | | | |
| | | Zero initialization | To initialize all bias terms to zero | | | |
| | | L2 regularization | To prevent overfitting | | | |
| | | GloVe | To initialize word embeddings | | | |
| | | Adam optimizer | To optimize the model | | | |

**Table 9** (continued)

| Studies | Research issue | Technologies used | Purpose of technology used | Effectiveness | TCS | MCS |
|---|---|---|---|---|---|---|
| [74] | Aspect term extraction | LSTM | To build initial aspect and opinion representations by recording sequential information | Effective in leveraging opinion summaries for improved aspect extraction. Effective in discovering uncommon aspects by utilizing history attention mechanisms | 114 | 19 |
| | | Truncated history attention (THA) | To encode historical information into aspect representations by distilling useful features from recent aspect predictions and generating history-aware aspect representations | | | |
| | | Selective transformation network (STN) | To obtain opinion summaries by applying aspect information to transform initial opinion representations and using attention over these transformed representations | | | |
| | | Bi-linear attention network | To calculate the opinion summary as a weighted sum of new opinion representations based on their associations with the current aspect representation | | | |
| | | GloVe | To initialize word embeddings | | | |
| | | Uniform distribution | To initialize embeddings for out-of-vocabulary words randomly sampled from the uniform distribution | | | |
| | | Glorot uniform initialization | To initialize the matrices in LSTMs using the Glorot Uniform strategy | | | |
| [64] | Aspect-based sentiment classification | GCN | To exploit syntactical information and word dependencies | Effective in demonstrating the insufficiency of directly integrating syntax information into the attention mechanism | 205 | 41 |
| | | Bi-LSTM | To capture contextual information regarding word order in sentences | | | |
| | | Multi-layered graph convolution structure | To encode and update the representation of nodes in the graph using features of immediate neighbors and to draw syntactically relevant words to the target aspect | | | |
| | | GloVe | To initialize word embeddings | | | |
| | | Uniform initialization | To initialize all model weights uniformly | | | |
| | | Adam optimizer | To optimize the model | | | |
| | | L2 regularization | To prevent overfitting | | | |

Table 9 (continued)

| Studies | Research issue | Technologies used | Purpose of technology used | Effectiveness | TCS | MCS |
|---|---|---|---|---|---|---|
| [65] | Aspect-level sentiment analysis | Bi-LSTM | To learn representations for features of a sentence by integrating context information in both forward and backward directions | Effective in encoding context and dependency information into aspect vectors for sentiment classification. Effective in propagating relevant information along the sequence of words and syntactic dependency paths | 169 | 33.8 |
| | | GCN | To enhance the embeddings learned by Bi-LSTM by integrating dependency information directly from the dependency tree of the sentence | | | |
| | | Dependency tree | To structure the sentence in a way that highlights syntactic relationships between words | | | |
| | | GloVe | To initialize word embeddings | | | |
| | | Part-of-speech (POS) embeddings | To incorporate syntactic information into the model by embedding POS tags | | | |
| | | Bi-LSTM | To capture contextual information for each word by learning embeddings | | | |
| | | Adam optimizer | To optimize the model parameters | | | |
| [60] | Aspect extraction and aspect sentiment classification | BERT | To initialize the word embeddings with pre-trained language model representations | Effective in improving aspect extraction by incorporating contextualized domain knowledge. Effective in enhancing classification across multiple review-based tasks through joint post-training | 285 | 57 |
| | | FP16 computation | To reduce the size of both the model and hidden representations of data | | | |
| | | Adam optimizer | To optimize the model parameters during training | | | |

**Table 9** (continued)

| Studies | Research issue | Technologies used | Purpose of technology used | Effectiveness | TCS | MCS |
|---|---|---|---|---|---|---|
| [78] | Aspect-level sentiment classification | Global lexical graph | To encode corpus-level word co-occurrence information | Effective in leveraging both syntactic and lexical graphs to improve classification and sentiment polarity identification | 95 | 23.75 |
| | | Hierarchical syntactic graph | To differentiate various types of dependency relations by grouping similar dependency types | | | |
| | | Hierarchical lexical graph | To distinguish different types of word co-occurrence relations | | | |
| | | Bi-level interactive graph convolution network | To fully exploit and integrate the information from both the syntactic and lexical graphs | | | |
| | | GloVe | To initialize word embeddings | | | |
| | | spaCy toolkit | To extract dependency relations from text | | | |
| | | Adam optimizer | To optimize the neural network | | | |
| | | L2 regularization | To prevent overfitting | | | |
| [79] | Aspect-level sentiment classification | Knowledge transfer from document-level data | To improve the performance of aspect-level sentiment classification by leveraging less expensive, document-level data | Effective in capturing domain-specific opinion words. Effective in handling sentences with negation words. Effective in recognizing neutral instances to compensate for the lack of aspect-level training examples | 107 | 17.83 |
| | | LSTM | To enhance aspect-level sentiment classification by integrating document-level knowledge | | | |
| | | GloVe | To initialize embeddings | | | |
| | | L2 regularization | To prevent overfitting by penalizing large weights | | | |
| | | RMSProp optimizer | To optimize the model parameters | | | |

**Table 9** (continued)

| Studies | Research issue | Technologies used | Purpose of technology used | Effectiveness | TCS | MCS |
|---|---|---|---|---|---|---|
| [80] | Aspect-level sentiment classification | Interactive attention networks (IAN) | To interactively learn attention in contexts and targets and generate their representations separately | Effective in interactively learning and modeling the representations of targets and contexts for sentiment classification. Effective in enhancing sentiment polarity prediction by fully considering the interaction between target and context | 494 | 70.57 |
| | | LSTM | To handle sequential data and capture long-term dependencies in the text for sentiment classification | | | |
| | | GloVe | To initialize word embeddings from context and target with pre-trained word vectors | | | |
| | | Uniform initialization | To initialize embeddings by sampling from a uniform distribution | | | |
| | | Zero initialization | To initialize all biases to zero | | | |
| | | Momentum optimization | To train the parameters of IAN | | | |
| | | L2 regularization | To prevent overfitting | | | |
| [66] | Aspect sentiment triplet extraction | Unified tagging system | To label aspect terms and sentiments using a unified tagging schema built on top of stacked Bi-LSTM networks | Effective in extracting aspects and their associated sentiments simultaneously. Effective in leveraging mutual information among aspect extraction, sentiment classification, and opinion term extraction to enhance overall performance. Effective in incorporating sentiment classification signals to aid in the accurate extraction of opinion terms | 104 | 26 |
| | | Bi-LSTM | To perform sequence tagging for aspect extraction, sentiment classification, and opinion term extraction by capturing contextual information in both directions | | | |
| | | BIO-like tagging system | To label opinion terms, providing a structured way to identify the beginning, inside, and outside of opinion expressions | | | |
| | | GCN | To utilize semantic and syntactic information in a sentence for opinion term tagging | | | |
| | | GloVe | To initialize word embeddings | | | |
| | | SGD optimizer | To train the model with a stochastic gradient descent algorithm | | | |

**Table 9** (continued)

| Studies | Research issue | Technologies used | Purpose of technology used | Effectiveness | TCS | MCS |
|---|---|---|---|---|---|---|
| [67] | Aspect-level sentiment classification | GCN | To capture sentiment dependencies between multiple aspects in one sentence | Effective in capturing sentiment dependencies between multiple aspects in one sentence. Effective in capturing interactive information among multiple aspects | 97 | 24.25 |
| | | Bi-LSTM | To capture the contextual information for each word | | | |
| | | GloVe | To initialize the word embeddings | | | |
| | | BERT | To initialize the word embeddings with pre-trained language model representations | | | |
| | | Normal distribution | To initialize the weight matrix of the last fully connected layer using a normal distribution | | | |
| | | Uniform distribution | To initialize all weight matrices (except the last fully connected layer) using a uniform distribution | | | |
| | | L2 regularization | To prevent overfitting | | | |
| | | Adam optimizer | To optimize the model parameters | | | |
| [73] | Aspect-level sentiment classification | Fine-grained attention mechanism | To capture the word-level interaction between aspect and context | Effective in linking and fusing information between context and aspect words. Effective in handling aspects with multiple words, reducing information loss in coarse-grained attention mechanisms. Effective in capturing aspect-level interactions to improve performance, especially in datasets with multiple aspects per sentence | 238 | 39.67 |
| | | Coarse-grained attention mechanism | To capture the overall interaction between aspect and context | | | |
| | | Multi-grained attention network (MGAN) | To combine fine-grained and coarse-grained attention mechanisms for comprehensive aspect-level sentiment analysis | | | |
| | | Bi-LSTM | To capture temporal interactions among words by processing sequences in both forward and backward directions | | | |
| | | GloVe | To initialize word embeddings for both context and aspect words | | | |
| | | Uniform initialization | To initialize the weight matrix and bias by sampling from a uniform distribution | | | |
| | | L2 regularization | To prevent overfitting | | | |

Table 9 (continued)

| Studies | Research issue | Technologies used | Purpose of technology used | Effectiveness | TCS | MCS |
|---|---|---|---|---|---|---|
| [69] | Aspect-based sentiment analysis | Dependency parsing | To obtain the dependency tree of a sentence | Effective in capturing important syntactic structures for sentiment analysis. Effective in handling multiple aspects within a single sentence, improving the accuracy across different semantic distance ranges | 211 | 52.75 |
| | | Relational graph attention network (R-GAT) | To encode the aspect-oriented dependency tree structure for sentiment prediction | | | |
| | | Graph attention network (GAT) | To generalize encoding graphs with labeled edges | | | |
| | | Bi-LSTM | To encode the word embeddings of tree nodes and the aspect words | | | |
| | | GloVe | To provide word embeddings for R-GAT | | | |
| | | BERT | To provide pre-trained word representations, with fine-tuning on the task | | | |
| | | Adam optimizer | To train the model with efficient gradient-based optimization | | | |
| [70] | Target-dependent aspect detection and targeted aspect-based polarity classification | LSTM | To model sequences and maintain long-term dependencies in the text data | Effective in significantly improving aspect detection. Effective in using target-level attention to identify parts of target expressions with higher sentiment salience | 187 | 31.17 |
| | | Stacked attention mechanism | To focus on different levels of information, specifically target-level and sentence-level | | | |
| | | Sentic LSTM | To integrate explicit commonsense knowledge with implicit knowledge within the LSTM architecture | | | |
| | | Recurrent additive network | To simulate semantic patterns and enhance the LSTM by modeling the additive effects of sentiments | | | |
| | | Syntax-based concept parser | To extract a set of concept candidates at each time step | | | |
| | | AffectiveSpace embedding | To provide concept embeddings that represent the affective aspects of the concepts | | | |

**Table 9** (continued)

| Studies | Research issue | Technologies used | Purpose of technology used | Effectiveness | TCS | MCS |
|---|---|---|---|---|---|---|
| [75] | Aspect-level sentiment classification | Syntax-based GCN | To model the syntactic dependency tree and enhance sentence representation toward a given aspect independently | Effective in incorporating syntactic dependency trees and knowledge graphs for aspect-level sentiment classification. Effective in enriching sentence representations toward given aspects | 91 | 22.75 |
| | | Knowledge-based GCN | To model commonsense knowledge graphs independently and enrich sentence representation toward a given aspect | | | |
| | | Bi-LSTM | To obtain contextualized word representations as input features for the GCN by modeling the sentence from the embeddings | | | |
| | | GloVe | To provide pre-trained word embeddings | | | |
| | | BERT | To generate contextualized word embeddings that capture the meaning of words in context | | | |
| | | Uniform initialization | To initialize all out-of-vocabulary words and weights with a uniform distribution | | | |
| | | Adam optimizer | To optimize the model parameters | | | |

**Table 9** (continued)

| Studies | Research issue | Technologies used | Purpose of technology used | Effectiveness | TCS | MCS |
|---|---|---|---|---|---|---|
| [61] | Aspect-level sentiment classification | Dependency graph | To represent a sentence as a dependency graph instead of a word sequence | Effective in leveraging dependency graphs to propagate sentiment features from syntax-dependent words to the aspect target. Effective in utilizing syntax information to improve sentiment classification performance | 116 | 23.2 |
| | | Graph attention network (GAT) | To propagate sentiment features from important syntax neighborhood words to the aspect target in the dependency graph | | | |
| | | LSTM | To explicitly capture aspect-related information across layers during recursive neighborhood expansion within the TD-GAT framework | | | |
| | | GloVe | To provide pre-trained word embeddings for initializing the model | | | |
| | | BERT | To incorporate deep contextualized word representations | | | |
| | | L2 regularization | To prevent overfitting by penalizing large weights | | | |
| | | Adam optimizer | To optimize the model parameters | | | |
| | | SGD optimizer | To fine-tune and stabilize the model after initial training with the Adam optimizer | | | |
| [62] | Target-dependent sentiment classification | BERT | To leverage pre-trained DL models that understand the context of words in a sentence by looking at the words before and after the target word | Effective in integrating target position output information into BERT models to enhance classification accuracy. Effective in applying information fusion techniques such as element-wise multiplication or concatenation to improve model performance | 155 | 31 |
| | | Target-dependent BERT | To enhance the BERT model by incorporating target-specific information for improved performance in aspect-level sentiment classification | | | |
| | | Adam optimizer | To optimize the model parameters | | | |

**Table 9** (continued)

| Studies | Research issue | Technologies used | Purpose of technology used | Effectiveness | TCS | MCS |
|---|---|---|---|---|---|---|
| [72] | Aspect-based sentiment analysis and targeted sentiment analysis | LSTM | To model the sequential dependencies in the data and capture long-term relationships within the text | Effective in using target- and aspect-dependent sentence attention to retrieve relevant information for both aspect categorization and sentiment classification. Effective in incorporating affective properties through knowledge integration | 330 | 55 |
| | | Hierarchical attention mechanism | To focus on target- and sentence-level information for more precise sentiment analysis | | | |
| | | Sentic LSTM | To extend the traditional LSTM by integrating commonsense knowledge tightly into the recurrent encoder | | | |
| | | Bi-LSTM | To process the input sequence in both forward and backward directions | | | |
| | | Pre-trained skip-gram model | To initialize the word embeddings | | | |
| [82] | Aspect-level sentiment classification | Feature capsules | To transform N-gram features into capsules that represent more complex patterns and features | Effective in transferring knowledge from document-level tasks. Effective in leveraging shared features across related tasks. Effective in utilizing multi-task learning variants to achieve robust performance despite label noise | 108 | 21.6 |
| | | Semantic capsules | To aggregate feature capsules into aspect-related sentence-level representations | | | |
| | | Class capsules | To generate capsules that correspond to sentiment polarities | | | |
| | | GloVe | To use pre-trained word embeddings for improved word representation | | | |
| | | Adam optimizer | To optimize the neural network | | | |
| [68] | Sentence-pair classification | BERT | To enhance the accuracy of TABSA by fine-tuning a pre-trained BERT model using its final hidden state representations and a classification layer | Effective in expanding the corpus by converting target and aspect information into auxiliary sentences. Effective in constructing auxiliary sentences for complex ABSA tasks | 248 | 49.6 |
| | | Auxiliary sentence construction | To create supplementary sentences that aid in transforming the (T)ABSA task into a sentence-pair classification task | | | |

**Table 9** (continued)

| Studies | Research issue | Technologies used | Purpose of technology used | Effectiveness | TCS | MCS |
|---|---|---|---|---|---|---|
| [63] | Domain aspect classification, aspect-term and opinion-word separation, and sentiment polarity classification | Word2Vec | To compute word embeddings for word similarity calculations | Effective in multilingual domain aspect classification. Effective in separating aspect terms from opinion words without additional supervision | 108 | 18 |
| | | Apache Spark MLlib | To implement and compute domain-based word embeddings efficiently | | | |
| | | LDA-based topic model | To identify and extract topics from text data, adapted with biased topic modeling parameters | | | |
| | | Maximum entropy classifier | To categorize sentences into predefined classes based on the learned distributions | | | |

*TCS* Total citations, *MCS* Mean citations

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## Declarations

**Informed Consent** Informed consent was not required as no human or animals were involved.

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## References

1. Ren M, Chen N, Qiu H. Human-machine collaborative decision-making: an evolutionary roadmap based on cognitive intelligence. Int J Soc Robot. 2023;15(7):1101–14.
2. Chamola V, Sai S, Sai R, Hussain A, Sikdar B. Generative AI for consumer electronics: enhancing user experience with cognitive and semantic computing. IEEE Consum Electron Mag. 2024;1–9. https://doi.org/10.1109/MCE.2024.3387049.
3. Zhong G, Jiao W, Gao W, Huang K. Automatic design of deep networks with neural blocks. Cognit Comput. 2020;12(1):1–12.
4. Yosipof A, Drori N, Elroy O, Pierraki Y. Textual sentiment analysis and description characteristics in crowdfunding success: the case of cybersecurity and IoT industries. Electron Mark. 2024;34(1):30.
5. He K, Mao R, Gong T, Li C, Cambria E. Meta-based self-training and re-weighting for aspect-based sentiment analysis. IEEE Trans Affect Comput. 2023;14(03):1731–42.
6. Dashtipour K, Gogate M, Gelbukh A, Hussain A. Extending persian sentiment lexicon with idiomatic expressions for sentiment analysis. Soc Netw Anal Min. 2022;12:1–13.

7. Lengkeek M, van der Knaap F, Frasincar F. Leveraging hierarchical language models for aspect-based sentiment analysis on financial data. Inf Process Manag. 2023;60(5):103435.
8. Kontonatsios G, Clive J, Harrison G, Metcalfe T, Sliwiak P, Tahir H, et al. FABSA: an aspect-based sentiment analysis dataset of user reviews. Neurocomputing. 2023;562:126867.
9. Chauhan GS, Nahta R, Meena YK, Gopalani D. Aspect based sentiment analysis using deep learning approaches: a survey. Comput Sci Rev. 2023;49:100576.
10. Karaoğlan KM, Fındık O. Extended rule-based opinion target extraction with a novel text pre-processing method and ensemble learning. Appl Soft Comput. 2022;118:108524.
11. Truşcă MM, Frasincar F. Survey on aspect detection for aspect-based sentiment analysis. Artif Intell Rev. 2023;56(5):3797–846.
12. Wang Y, Liu L, Wang C. Trends in using deep learning algorithms in biomedical prediction systems. Front Neurosci. 2023;17:1256351.
13. Zhang W, Li X, Deng Y, Bing L, Lam W. A survey on aspect-based sentiment analysis: tasks, methods, and challenges. IEEE Trans Knowl Data Eng. 2023;35(11):11019–38.
14. Sohangir S, Wang D, Pomeranets A, Khoshgoftaar TM. Big data: deep learning for financial sentiment analysis. J Big Data. 2018;5(1):1–25.
15. Mahmud M, Kaiser MS, McGinnity TM, Hussain A. Deep learning in mining biological data. Cognit Comput. 2021;13(1):1–33.
16. Anas M, Saiyeda A, Sohail S, Cambria E, Hussain A. Can generative AI models extract deeper sentiments as compared to traditional deep learning algorithms? IEEE Intell Syst. 2024;39(2):5–10.
17. Lu Q, Sun X, Long Y, Gao Z, Feng J, Sun T. Sentiment analysis: comprehensive reviews, recent advances, and open challenges. IEEE Trans Neural Netw Learn Syst. 2023;1–21. https://doi.org/10.1109/TNNLS.2023.3294810.
18. Fan C, Lin J, Mao R, Cambria E. Fusing pairwise modalities for emotion recognition in conversations. Inf Fusion. 2024;106:102306.
19. Alzubaidi L, Bai J, Al-Sabaawi A, Santamaría J, Albahri AS, Al-dabbagh BSN, et al. A survey on deep learning tools dealing with data scarcity: definitions, challenges, solutions, tips, and applications. J Big Data. 2023;10(1):46.
20. Zhang Y, Yang Y, Liang B, Chen S, Qin B, Xu R. An empirical study of sentiment-enhanced pre-training for aspect-based sentiment analysis. In: Findings of the Association for Computational Linguistics: ACL 2023. 2023. p. 9633–51.
21. Nazir A, Rao Y, Wu L, Sun L. Issues and challenges of aspect-based sentiment analysis: a comprehensive survey. IEEE Trans Affect Comput. 2020;13(2):845–63.
22. Fei H, Ren Y, Zhang Y, Ji D. Nonautoregressive encoder–decoder neural framework for end-to-end aspect-based sentiment triplet extraction. IEEE Trans Neural Netw Learn Syst. 2021;34(9):5544–56.
23. Zhang J, Yin Z, Chen P, Nichele S. Emotion recognition using multi-modal data and machine learning techniques: a tutorial and review. Inf Fusion. 2020;59:103–26.
24. Riaz A, Gregor S, Dewan S, Xu Q. The interplay between emotion, cognition and information recall from websites with relevant and irrelevant images: a Neuro-IS study. Decis Support Syst. 2018;111:113–23.
25. Huang F, Li X, Yuan C, Zhang S, Zhang J, Qiao S. Attention-emotion-enhanced convolutional LSTM for sentiment analysis. IEEE Trans Neural Netw Learn Syst. 2021;33(9):4332–45.
26. Jung-Beeman M. Bilateral brain processes for comprehending natural language. Trends Cogn Sci. 2005;9(11):512–8.
27. Chen J, Huang Z, Xue Y. Bilateral-brain-like semantic and syntactic cognitive network for aspect-level sentiment analysis. In: 2021 International Joint Conference on Neural Networks (IJCNN). 2021. p. 1–8 IEEE.
28. Zhu R, Liu L, Ma M, Li H. Cognitive-inspired computing: advances and novel applications. Futur Gener Comp Syst. 2020;109:706–9.
29. Poria S, Cambria E, Bajpai R, Hussain A. A review of affective computing: From unimodal analysis to multimodal fusion. Inf Fusion. 2017;37:98–125.
30. Jain DK, Boyapati P, Venkatesh J, Prakash M. An intelligent cognitive-inspired computing with big data analytics framework for sentiment analysis and classification. Inf Process Manag. 2022;59(1):102578.
31. Li Y, Zhang K, Wang J, Gao X. A cognitive brain model for multimodal sentiment analysis based on attention neural networks. Neurocomputing. 2021;430:159–73.
32. Rahmani S, Hosseini S, Zall R, Kangavari MR, Kamran S, Hua W. Transfer-based adaptive tree for multimodal sentiment analysis based on user latent aspects. Knowledge-Based Syst. 2023;261:110219.
33. Diwali A, Saeedi K, Dashtipour K, Gogate M, Cambria E, Hussain A. Sentiment analysis meets explainable artificial intelligence: a survey on explainable sentiment analysis. IEEE Trans Affect Comput. 2023;1–12. https://doi.org/10.1109/TAFFC.2023.3296373.
34. Bensoltane R, Zaki T. Aspect-based sentiment analysis: an overview in the use of Arabic language. Artif Intell Rev. 2023;56(3):2325–63.
35. Do HH, Prasad PWC, Maag A, Alsadoon A. Deep learning for aspect-based sentiment analysis: a comparative review. Expert Syst Appl. 2019;118:272–99.
36. Trisna KW, Jie HJ. Deep learning approach for aspect-based sentiment classification: a comparative review. Appl Artif Intell. 2022;36(1):2014186.
37. Liu H, Chatterjee I, Zhou M, Lu XS, Abusorrah A. Aspect-based sentiment analysis: a survey of deep learning methods. IEEE Trans Comput Soc Syst. 2020;7(6):1358–75.
38. Dwivedi YK, Sharma A, Rana NP, Giannakis M, Goel P, Dutot V. Evolution of artificial intelligence research in technological forecasting and social change: research topics, trends, and future directions. Technol Forecast Soc Change. 2023;192:122579.
39. Camacho D, Panizo-LLedot A, Bello-Orgaz G, Gonzalez-Pardo A, Cambria E. The four dimensions of social network analysis: an overview of research methods, applications, and software tools. Inf Fusion. 2020;63:88–120.
40. Chen X, Xie H. A structural topic modeling-based bibliometric study of sentiment analysis literature. Cognit Comput. 2020;12:1097–129.
41. Chen X, Xie H, Hwang G-J. A multi-perspective study on artificial intelligence in education: grants, conferences, journals, software tools, institutions, and researchers. Comput Educ Artif Intell. 2020;1:100005.
42. Dong M, Li F, Chang H. Trends and hotspots in critical thinking research over the past two decades: insights from a bibliometric analysis. Heliyon. 2023;9(6):e16934.
43. Chen X, Xie H, Tao X, Xu L, Wang J, Dai H, et al. A topic modeling-based bibliometric exploration of automatic summarization research. Wiley Interdiscip Rev Data Min Knowl Discov. 2024;e1540. https://doi.org/10.1002/widm.1540.
44. Mostaghel R, Oghazi P, Parida V, Sohrabpour V. Digitalization driven retail business model innovation: evaluation of past and avenues for future research trends. J Bus Res. 2022;146:134–45.
45. Kumar V, Srivastava A. Trends in the thematic landscape of corporate social responsibility research: a structural topic modeling approach. J Bus Res. 2022;150:26–37.
46. Chen X, Zou D, Cheng G, Xie H. Detecting latent topics and trends in educational technologies over four decades using structural topic modeling: a retrospective of all volumes of computer & education. Comput Educ. 2020;151:103855.

47. Anselin L, Syabri I, Kho Y. GeoDa: an introduction to spatial data analysis. In: Handbook of applied spatial analysis: Software tools, methods and applications. Springer; 2009. p. 73–89.
48. Bastian M, Heymann S, Jacomy M. Gephi: an open source software for exploring and manipulating networks. In: Proceedings of the Third International AAAI Conference on Weblogs and Social Media. 2009. p. 361–2.
49. Roberts ME, Stewart BM, Tingley D. Stm: an R package for structural topic models. J Stat Softw. 2019;91:1–40.
50. Zhao T, Liu H, Roeder K, Lafferty J, Wasserman L. The huge package for high-dimensional undirected graph estimation in R. J Mach Learn Res. 2012;13(Apr):1059–62.
51. Chen X, Zou D, Xie H. A decade of learning analytics: structural topic modeling based bibliometric analysis. Educ Inf Technol. 2022;27(8):10517–61.
52. Minaee S, Kalchbrenner N, Cambria E, Nikzad N, Chenaghlu M, Gao J. Deep learning based text classification: a comprehensive review. ACM Comput Surv. 2023;54(3):1–40.
53. Khan W, Daud A, Khan K, Muhammad S, Haq R. Exploring the frontiers of deep learning and natural language processing: a comprehensive overview of key challenges and emerging trends. Nat Lang Process J. 2023;4: 100026.
54. Yusuf A, Sarlan A, Danyaro KU, Rahman ASBA, Abdullahi M. Sentiment analysis in low-resource settings: a comprehensive review of approaches, languages, and data sources. IEEE Access. 2024;12:66883–909.
55. Deng J, Ren F. A survey of textual emotion recognition and its challenges. IEEE Trans Affect Comput. 2021;14(1):49–67.
56. Alturayeif N, Aljamaan H, Hassine J. An automated approach to aspect-based sentiment analysis of apps reviews using machine and deep learning. Autom Softw Eng. 2023;30(2):30.
57. Chen X, Tao X, Wang FL, Xie H. Global research on artificial intelligence-enhanced human electroencephalogram analysis. Neural Comput Appl. 2022;34(14):11295–333.
58. Liang B, Su H, Gui L, Cambria E, Xu R. Aspect-based sentiment analysis via affective knowledge enhanced graph convolutional networks. Knowledge-Based Syst. 2022;235:107643.
59. Ray B, Garain A, Sarkar R. An ensemble-based hotel recommender system using sentiment analysis and aspect categorization of hotel reviews. Appl Soft Comput. 2021;98:106935.
60. Xu H, Liu B, Shu L, Yu PS. BERT post-training for review reading comprehension and aspect-based sentiment analysis. In: Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. 2019. p. 2324–35.
61. Huang B, Carley KM. Syntax-aware aspect level sentiment classification with graph attention networks. In: Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP). 2019. p. 5469–77.
62. Gao Z, Feng A, Song X, Wu X. Target-dependent sentiment classification with BERT. IEEE Access. 2019;7:154290–9.
63. García-Pablos A, Cuadros M, Rigau G. W2VLDA: almost unsupervised system for aspect based sentiment analysis. Expert Syst Appl. 2018;91:127–37.
64. Zhang C, Li Q, Song D. Aspect-based sentiment classification with aspect-specific graph convolutional networks. In: Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP). 2019. p. 4568–78.
65. Sun K, Zhang R, Mensah S, Mao Y, Liu X. Aspect-level sentiment analysis via convolution over dependency tree. In: Proceedings of the 2019 conference on empirical methods in natural language processing and the 9th international joint conference on natural language processing (EMNLP-IJCNLP). 2019. p. 5679–88.
66. Peng H, Xu L, Bing L, Huang F, Lu W, Si L. Knowing what, how and why: a near complete solution for aspect-based sentiment analysis. In: Proceedings of the AAAI Conference on Artificial Intelligence. 2020. p. 8600–7.
67. Zhao Q, Yang F, An D, Lian J. Modeling structured dependency tree with graph convolutional networks for aspect-level sentiment classification. Sensors. 2024;24(2):418.
68. Sun C, Huang L, Qui X. Utilizing BERT for aspect-based sentiment analysis via constructing auxiliary sentence. In: Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, vol. 1. 2019. p. 380–5.
69. Wang K, Shen W, Yang Y, Quan X, Wang R. Relational graph attention network for aspect-based sentiment analysis. In: Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics. 2020. p. 3229–38.
70. Ma Y, Peng H, Khan T, Cambria E, Hussain A. Sentic LSTM: a hybrid network for targeted aspect-based sentiment analysis. Cognit Comput. 2018;10(4):639–50.
71. Xue W, Li T. Aspect based sentiment analysis with gated convolutional networks. In: Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics, vol. 1. 2018. p. 2514–23.
72. Ma Y, Peng H, Cambria E. Targeted aspect-based sentiment analysis via embedding commonsense knowledge into an attentive LSTM. In: Thirty-Second AAAI Conference on Artificial Intelligence. 2018. p. 5876–83.
73. Fan F, Feng Y, Zhao D. Multi-grained attention network for aspect-level sentiment classification. In: Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing. 2018. p. 3433–42.
74. Li X, Bing L, Lam W, Yang Z. Aspect term extraction with history attention and selective transformation. In: Proceedings of the 27th International Joint Conference on Artificial Intelligence. 2018. p. 4194–200.
75. Zhou J, Huang JX, Hu QV, He L. Sk-gcn: modeling syntax and knowledge via graph convolutional network for aspect-level sentiment classification. Knowledge-Based Syst. 2020;205:106292.
76. He R, Lee WS, Ng HT, Dahlmeier D. An unsupervised neural attention model for aspect extraction. In: Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, vol. 1. 2017. p. 388–97.
77. Huang B, Ou Y, Carley KM. Aspect level sentiment classification with attention-over-attention neural networks. In: Proceedings of the 11th International Conference on Social, Cultural, and Behavioral Modeling. 2018. p. 197–206.
78. Zhang M, Qian T. Convolution over hierarchical syntactic and lexical graphs for aspect level sentiment analysis. In: Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP). 2020. p. 3540–9.
79. He R, Lee WS, Ng HT, Dahlmeier D. Exploiting document knowledge for aspect-level sentiment classification. In: Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics, vol. 2. 2018. p. 579–85.
80. Ma D, Li S, Zhang X, Wang H. Interactive attention networks for aspect-level sentiment classification. In: Proceedings of the 26th International Joint Conference on Artificial Intelligence. 2017. p. 4068–74.
81. He R, Lee WS, Ng HT, Dahlmeier D. An interactive multi-task learning network for end-to-end aspect-based sentiment analysis. In: Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics. 2019. p. 504–15.

82. Chen Z, Qian T. Transfer capsule network for aspect level sentiment classification. In: Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics. 2019. p. 547–56.
83. Wang G, He J. A bibliometric analysis of recent developments and trends in knowledge graph research (2013–2022). IEEE Access. 2024;12:32005–13.
84. Chen X, Xie H, Wang J, Li Z, Cheng G, Wong ML, et al. A bibliometric review of soft computing for recommender systems and sentiment analysis. IEEE Trans Artif Intell. 2021;3(5):642–56.
85. Azer SA, Azer S. Top-cited articles in medical professionalism: a bibliometric analysis versus altmetric scores. BMJ Open. 2019;9(7):e029433.
86. Mohsen MA. A bibliometric study of the applied linguistics research output of Saudi institutions in the Web of Science for the decade 2011–2020. Electron Libr. 2021;39(6):865–84.
87. Chen X, Zou D, Xie H, Cheng G, Liu C. Two decades of artificial intelligence in education: contributors, collaborations, research topics, challenges, and future directions. Educ Technol Soc. 2022;25(1):28–47.
88. Khanal S, Zhang H, Taeihagh A. Development of new generation of artificial intelligence in China: when Beijing's global ambitions meet local realities. J Contemp China. 2024;1–24. https://doi.org/10.1080/10670564.2024.2333492.
89. Guerrero Bote VP, Olmeda-Gómez C, de Moya-Anegón F. Quantifying the benefits of international scientific collaboration. J Am Soc Inf Sci Technol. 2013;64(2):392–404.
90. Ke Q. Interdisciplinary research and technological impact: evidence from biomedicine. Scientometrics. 2023;128(4):2035–77.
91. Ozenc-Ira G. Mapping research on musical creativity: a bibliometric review of the literature from 1990 to 2022. Think Ski Creat. 2023;48:101273.
92. Hernández-Torrano D, Ibrayeva L. Creativity and education: a bibliometric mapping of the research literature (1975–2019). Think Ski Creat. 2020;35:100625.
93. Mewada A, Dewang RK. SA-ASBA: a hybrid model for aspect-based sentiment analysis using synthetic attention in pre-trained language BERT model with extreme gradient boosting. J Supercomput. 2023;79(5):5516–51.
94. Abdelgwad MM, Soliman THA, Taloba AI. Arabic aspect sentiment polarity classification using BERT. J Big Data. 2022;9(1):115.
95. Aziz MM, Bakar AA, Yaakub MR. CoreNLP dependency parsing and pattern identification for enhanced opinion mining in aspect-based sentiment analysis. J King Saud Univ Inf Sci. 2024;36(4):102035.
96. Xiang C, Zhang J, Zhou J, Li F, Teng C, Ji D. Phrase-aware financial sentiment analysis based on constituent syntax. IEEE/ACM Trans Audio, Speech, Lang Process. 2024;32:1994–2005.
97. Zeng Y, Li Z, Chen Z, Ma H. Aspect-level sentiment analysis based on semantic heterogeneous graph convolutional network. Front Comput Sci. 2023;17(6):176340.
98. Liang Y, Meng F, Zhang J, Chen Y, Xu J, Zhou J. A dependency syntactic knowledge augmented interactive architecture for end-to-end aspect-based sentiment analysis. Neurocomputing. 2021;454:291–302.
99. Zhang Q, Wang S, Li J. A contrastive learning framework with tree-LSTMs for aspect-based sentiment analysis. Neural Process Lett. 2023;55(7):8869–86.
100. Zou W, Zhang W, Tian Z, Wu W. A syntactic features and interactive learning model for aspect-based sentiment analysis. Complex Intell Syst. 2024;10:5359–77. https://doi.org/10.1007/s40747-024-01449-5.
101. Alomari A, Idris N, Sabri AQM, Alsmadi I. Deep reinforcement and transfer learning for abstractive text summarization: a review. Comput Speech Lang. 2022;71:101276.
102. Grewal R, Gupta S, Hamilton R. Marketing insights from multimedia data: text, image, audio, and video. J Mark Res. 2021;58(6):1025–33.
103. Hazmoune S, Bougamouza F. Using transformers for multimodal emotion recognition: taxonomies and state of the art review. Eng Appl Artif Intell. 2024;133:108339.
104. Yao C, Song X, Zhang X, Zhao W, Feng A. Multitask learning for aspect-based sentiment classification. Sci Program. 2021;2021:1–9.
105. Antonakaki D, Fragopoulou P, Ioannidis S. A survey of Twitter research: data model, graph structure, sentiment analysis and attacks. Expert Syst Appl. 2021;164:114006.
106. Zhang Y, Du J, Ma X, Wen H, Fortino G. Aspect-based sentiment analysis for user reviews. Cognit Comput. 2021;13(5):1114–27.
107. López M, Valdivia A, Martínez-Cámara E, Luzón MV, Herrera F. E2SAM: evolutionary ensemble of sentiment analysis methods for domain adaptation. Inf Sci (Ny). 2019;480:273–86.
108. Rietzler A, Stabinger S, Opitz P, Engl S. Adapt or get left behind: domain adaptation through BERT language model finetuning for aspect-target sentiment classification. In: Proceedings of the Twelfth Language Resources and Evaluation Conference. 2020. p. 4933–41.
109. Knoester J, Frasincar F, Trușcă MM. Cross-domain aspect-based sentiment analysis using domain adversarial training. World Wide Web. 2023;26(6):4047–67.
110. Phan HT, Nguyen NT, Hwang D. Convolutional attention neural network over graph structures for improving the performance of aspect-level sentiment analysis. Inf Sci (Ny). 2022;589:416–39.
111. Zhang T, Lin H, Xu B, Yang L, Wang J, Duan X. Adversarial neural network with sentiment-aware attention for detecting adverse drug reactions. J Biomed Inform. 2021;123:103896.
112. Mehra P. Unexpected surprise: emotion analysis and aspect based sentiment analysis (ABSA) of user generated comments to study behavioral intentions of tourists. Tour Manag Perspect. 2023;45:101063.
113. Chang Y-C, Ku C-H, Le Nguyen D-D. Predicting aspect-based sentiment using deep learning and information visualization: the impact of COVID-19 on the airline industry. Inf Manag. 2022;59(2):103587.
114. Qi R-H, Yang M-X, Jian Y, Li Z-G, Chen H. A local context focus learning model for joint multi-task using syntactic dependency relative distance. Appl Intell. 2023;53(4):4145–61.
115. Tembhurne JV, Diwan T. Sentiment analysis in textual, visual and multimodal inputs using recurrent neural networks. Multimed Tools Appl. 2021;80(5):6871–910.
116. Zhang J, Sun X, Li Y. Mining syntactic relationships via recursion and wandering on A dependency tree for aspect-based sentiment analysis. In: 2022 International Joint Conference on Neural Networks (IJCNN). 2022. p. 1–8 IEEE.
117. Poria S, Hazarika D, Majumder N, Mihalcea R. Beneath the tip of the iceberg: current challenges and new directions in sentiment analysis research. IEEE Trans Affect Comput. 2020;14(1):108–32.
118. Wibawa AP, Kurniawan F. A survey of text summarization: techniques, evaluation and challenges. Nat Lang Process J. 2024;7:100070.
119. Zarandi AK, Mirzaei S. A survey of aspect-based sentiment analysis classification with a focus on graph neural network methods. Multimed tools Appl. 2024;83:56619–95.https://doi.org/10.1007/s11042-023-17701-y.
120. Gandhi A, Adhvaryu K, Poria S, Cambria E, Hussain A. Multimodal sentiment analysis: a systematic review of history, datasets, multimodal fusion methods, applications, challenges and future directions. Inf Fusion. 2023;91:424–44.

121. Ji Y, Liu H, He B, Xiao X, Wu H, Yu Y. Diversified multiple instance learning for document-level multi-aspect sentiment classification. In: Proceedings of the 2020 conference on empirical methods in natural language processing (EMNLP). 2020. p. 7012–23.
122. Wang X, Xu G, Zhang Z, Jin L, Sun X. End-to-end aspect-based sentiment analysis with hierarchical multi-task learning. Neurocomputing. 2021;455:178–88.
123. Mao R, Li X. Bridging towers of multi-task learning with a gating mechanism for aspect-based sentiment analysis and sequential metaphor identification. In: Proceedings of the AAAI Conference on Artificial Intelligence. 2021. p. 13534–42.
124. Tan Z, Luo L, Zhong J. Knowledge transfer in evolutionary multi-task optimization: a survey. Appl Soft Comput. 2023;138:110182.
125. Rani S, Jain A. Aspect-based sentiment analysis of drug reviews using multi-task learning based dual BiLSTM model. Multimed Tools Appl. 2024;83(8):22473–501.
126. Vashishtha S, Gupta V, Mittal M. Sentiment analysis using fuzzy logic: a comprehensive literature review. Wiley Interdiscip Rev Data Min Knowl Discov. 2023;13(5):e1509.
127. Birjali M, Kasri M, Beni-Hssane A. A comprehensive survey on sentiment analysis: approaches, challenges and trends. Knowledge-Based Syst. 2021;226:107134.
128. Yang M, Yin W, Qu Q, Tu W, Shen Y, Chen X. Neural attentive network for cross-domain aspect-level sentiment classification. IEEE Trans Affect Comput. 2019;12(3):761–75.
129. Chen Z, Qian T. Retrieve-and-edit domain adaptation for end2end aspect based sentiment analysis. IEEE/ACM Trans Audio Speech Lang Process. 2022;30:659–72.
130. An W, Tian F, Chen P, Zheng Q. Aspect-based sentiment analysis with heterogeneous graph neural network. IEEE Trans Comput Soc Syst. 2022;10(1):403–12.
131. Han Y, Liu M, Jing W. Aspect-level drug reviews sentiment analysis based on double BiGRU and knowledge transfer. IEEE Access. 2020;8:21314–25.
132. Imani M, Noferesti S. Aspect extraction and classification for sentiment analysis in drug reviews. J Intell Inf Syst. 2022;59(3):613–33.
133. Shaik T, Tao X, Li L, Xie H, Velásquez JD. A survey of multimodal information fusion for smart healthcare: mapping the journey from data to wisdom. Inf Fusion. 2024;102:102040. https://doi.org/10.1016/j.inffus.2023.102040.
134. Wang H-C, Justitia A, Wang C-W. AsCDPR: a novel framework for ratings and personalized preference hotel recommendation using cross-domain and aspect-based features. Data Technol Appl. 2023;58(2):293–317.
135. Sindhu I, Daudpota SM, Badar K, Bakhtyar M, Baber J, Nurunnabi M. Aspect-based opinion mining on student's feedback for faculty teaching performance evaluation. IEEE Access. 2019;7:108729–41.
136. Ren P, Yang L, Luo F. Automatic scoring of student feedback for teaching evaluation based on aspect-level sentiment analysis. Educ Inf Technol. 2023;28(1):797–814.
137. Zhang J, Lu X, Liu D. Deriving customer preferences for hotels based on aspect-level sentiment analysis of online reviews. Electron Commer Res Appl. 2021;49:101094.
138. Yadav A, Vishwakarma DK. Sentiment analysis using deep learning architectures: a review. Artif Intell Rev. 2020;53(6):4335–85.
139. Kumar N, Hanji BR. Aspect-based sentiment score and star rating prediction for travel destination using multinomial logistic regression with fuzzy domain ontology algorithm. Expert Syst Appl. 2024;240: 122493.
140. Hammi S, Hammami SM, Belguith LH. Advancing aspect-based sentiment analysis with a novel architecture combining deep learning models CNN and bi-RNN with the machine learning model SVM. Soc Netw Anal Min. 2023;13(1):117.
141. Shi J, Li W, Bai Q, Yang Y, Jiang J. Syntax-enhanced aspect-based sentiment analysis with multi-layer attention. Neurocomputing. 2023;557:126730.
142. Binder M, Heinrich B, Hopf M, Schiller A. Global reconstruction of language models with linguistic rules–explainable AI for online consumer reviews. Electron Mark. 2022;32(4):2123–38.
143. Wu H, Zhou D, Sun C, Zhang Z, Ding Y, Chen Y. LSOIT: lexicon and syntax enhanced opinion induction tree for aspect-based sentiment analysis. Expert Syst Appl. 2024;235:121137.