

# Aspect-based Sentiment Analysis: A Bibliometric Review using Bibliometrix to Map Research Trends and Algorithm Methods

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## Abstract

This study presents a bibliometric overview of research trends and algorithmic models in Aspect-Based Sentiment Analysis (ABSA). Data were collected from the Scopus database, resulting in a dataset of 2,344 journal articles published between 2021 and early 2026. The analysis was conducted using the Bibliometrix and Biblioshiny packages in R to perform number of publications per year, source's production over time, country production over time, keyword co-occurrence, thematic mapping and evolution of research themes. The results show that ABSA research has experienced rapid growth with an annual publication increase of more than 30%. This study identifies BERT algorithmic models and Graph Convolutional Networks (GCN) as the most dominant supporting tools in the research literature. Thematic maps show that transformer-based techniques and attention mechanisms have emerged as key driving themes in this field. Furthermore, thematic evolution maps reveal a shift in focus from technical aspect extraction to online public opinion analysis, reinforced by the sharp surge in the use of Large Language Models (LLMs) in recent years. The findings provide a structured overview of the intellectual landscape of ABSA, clarifying dominant research clusters, methodological trajectories, and emerging themes. By highlighting the central role of transformer architectures, graph-based neural networks, and LLM integration, this study offers methodological guidance for future model development. Furthermore, the bibliometric insights reduce research fragmentation and identify underexplored directions, offering valuable insights for researchers to identify research gaps and develop more advanced ABSA models in future studies.

**Keywords:** aspect-based sentiment analysis, bibliometric review, deep learning, large language models, research trends

## 1 Introduction

The rapid development of digital technology and social media has generated enormous volumes of text data, including user opinions, reviews, and expressions of attitudes toward various products, services, and public issues [1]. This condition has driven increasing attention to sentiment analysis as an important approach in natural language processing (NLP) to extract opinions and emotions from text data. Sentiment analysis has been widely used in various domains, such as marketing, e-commerce, tourism, and public policy, due to its ability to support data-driven decision making [2].

However, traditional sentiment analysis approaches that focus on the document or sentence level are often unable to capture the complexity of multidimensional opinions [3]. In response to these limitations, Aspect-Based Sentiment Analysis (ABSA) was introduced to identify sentiments toward specific aspects or attributes of an entity. ABSA enables more granular opinion analysis, for example, distinguishing user sentiments toward quality, price, and service within the same product review [4], [5]. Bibliometric studies on sentiment analysis confirm the surge in ABSA publications, with aspect-based being the most frequently used approach due to its ability to capture semantic nuances without manual feature engineering [6]. This approach is considered more relevant and informative than conventional sentiment analysis, especially in the context of context-rich review and social media data [7], [8].

Various studies have shown that ABSA is increasingly being applied to real-world domains such as e-commerce, public opinion, academic services, and large-scale social media analysis, confirming the practical relevance of this approach [9], [10]. Over time, the methods and models used in ABSA have also undergone significant evolution. Early research relied heavily on lexicon- and rule-based

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approaches, then shifted to classic machine learning methods such as Support Vector Machines and Naïve Bayes [11], [12]. In recent years, the development of deep learning and transformer-based models such as BERT has dominated ABSA research due to their ability to represent semantic context more deeply [13], [14], [15]. This shift has not only improved model performance but also expanded ABSA's application to more complex languages and domains.

Despite the rapid growth of ABSA research projects, most previous studies have focused on the development and evaluation of specific algorithmic models. Studies that systematically map research trends, publication dynamics, global research contributions, and the development of ABSA algorithmic models are still relatively limited, especially for the most recent period. However, bibliometric mapping is crucial for providing a comprehensive overview of research development directions, key actors, and future research opportunities [16]. Furthermore, existing bibliometric studies often analyze sentiment analysis in general rather than specifically focusing on Aspect-Based Sentiment Analysis. As a result, a comprehensive understanding of how ABSA research has evolved is still lacking. Several recent systematic reviews also emphasize the need for bibliometric-based quantitative analysis to understand the direction of ABSA research globally and sustainably [17].

Based on these conditions, this study aims to conduct a bibliometric review of ABSA research for the period 2021–2025. This study maps publication trends, primary journal sources, country and institutional contributions, and the development of models and algorithms used in ABSA. It is hoped that the results of this study will provide an understanding of current ABSA research and serve as a reference for researchers in identifying research gaps and future development directions.

## **2 Literature Review**

Aspect-Based Sentiment Analysis (ABSA) has emerged as an important research area within natural language processing due to its ability to capture fine-grained opinions toward specific aspects of an entity. Recent empirical studies highlight that ABSA is increasingly positioned as a primary method for capturing complex opinion structures in review texts and social media, especially when a single entity is evaluated across multiple aspects with varying polarities [13], [18]. The complexities of natural language such as multi-aspect opinions, semantic ambiguity, and context dependencies are key factors driving the increased interest in ABSA over conventional sentiment analysis [19]. This shift reflects the growing need for sentiment analysis approaches capable of representing context dependencies and relationships between aspects more precisely, which cannot be achieved by document- or sentence-level sentiment analysis [20].

One of the major challenges in ABSA is the inherent complexity of natural language, including implicit sentiment expressions and multiple aspects within a single sentence. Addressing these challenges requires models that can capture contextual dependencies between aspects and opinion terms. Consequently, recent studies have explored advanced neural architectures capable of modeling long-range contextual relationships within text. In particular, pre-trained language models have demonstrated significant improvements in aspect-based sentiment classification compared to traditional machine learning approaches [21]. Furthermore, the integration of language models with graph-based approaches allows for a more explicit representation of syntactic and semantic relationships between aspects, thereby enhancing the model's ability to handle implicit opinions and long-range dependencies in text [22].

Beyond methodological developments, recent literature also highlights the rapid expansion of ABSA applications across various domains. Empirical studies show that ABSA is widely used to analyze large-scale product reviews, digital service evaluations, and public opinions expressed on social media platforms [23]. These applications demonstrate the practical relevance of ABSA for understanding user perceptions and decision-making behavior in digital environments. However, most of these studies primarily focus on improving model performance within specific datasets, rather than examining the broader development of the ABSA research field.

On the other hand, bibliometric approaches have been widely used to map research developments in sentiment analysis and natural language processing in general. Bibliometric studies have shown that quantitative analyses based on citations and co-occurrence are capable of identifying research trends, key actors, and mature and emerging themes [16]. However, bibliometric research specifically

focused on ABSA, particularly linking publication trends to the evolution of algorithmic models, remains relatively limited.

Based on this gap, this study conducts a comprehensive bibliometric analysis of ABSA research for the 2021–2025 period. This study begins with the assumption that ABSA research growth is reflected not only in the increasing number of publications but also in the consolidation of the transformer-based model as the dominant paradigm and the concentration of research contributions in specific countries and institutions. Therefore, this study focuses on mapping publication trends and the development of ABSA's algorithmic model, a key contribution that has not been comprehensively discussed in previous research. By consolidating fragmented findings into a coherent research map, this study offers strategic guidance for future methodological development and more globally informed research planning in the ABSA domain.

### 3 Research Method

#### Data Sources and Search Strategy

The bibliographic data in this study was obtained exclusively from the Scopus database. Scopus was chosen because of its extensive coverage of reputable scientific journals and its peer-reviewed nature across various disciplines. Furthermore, Scopus provides structured metadata and citation information, supporting comprehensive bibliometric analysis.

Data collection was conducted on January 20, 2026, so all articles indexed in Scopus from 2021 up to that date were included in this study. A literature search was conducted using the keyword "aspect-based sentiment analysis" to obtain publications focused on the ABSA topic. The search was conducted using the title, abstract, and author keywords to ensure comprehensive data coverage.

All bibliographic data is then exported in two formats: BibTeX (.bib) and Comma-Separated Values (CSV). The BibTeX format is used to ensure full compatibility with the Bibliometrix and Biblioshiny packages, while the CSV format is used for data checking using Microsoft Excel.

#### Inclusion and Exclusion Criteria

To ensure the relevance and quality of the data analyzed, this study applies the inclusion and exclusion criteria in Table 1.

**Table 1 Inclusion and exclusion criteria**

Inclusion Criteria	Exclusion Criteria
Journal articles that have undergone peer-review and are indexed in Scopus.	Documents other than journal articles, such as conference papers, reviews, book chapters, etc.
Publications that explicitly discuss Aspect-Based Sentiment Analysis.	Articles that are not directly relevant to ABSA despite having similar keywords.
Articles published within the research period.	Publications outside the research timeframe.

#### Bibliometric Analysis Techniques

This research employs several bibliometric analysis techniques, namely:

- Number of publications per year
- Source's production over time
- Country production over time
- Keyword co-occurrence analysis
- Thematic mapping and evolution of research themes
- Frequency of model use

Bibliometric analysis results were visualized using Biblioshiny, which provides various interactive graphical representations. Additionally, Microsoft Excel was used to enhance the display of tables and graphs for clarity and ease of understanding.

#### Research Flow

In summary, the flow of this research can be seen in Figure 1.



Figure 1 Research flow

## 4 Results and Analysis

This section presents and analyzes the bibliometric findings derived from 2,344 Scopus-indexed journal articles on Aspect-Based Sentiment Analysis (ABSA) published between 2021 and 2026. Each subsection discusses a specific dimension of the bibliometric analysis, including publication trends, source and country contributions, keyword co-occurrence patterns, thematic evolution, and the frequency of algorithmic model use.

### Number of Publications Per Year

Based on the bibliometric statistics summary in Figure 2, this research dataset includes 2,344 journal articles on Aspect-Based Sentiment Analysis (ABSA) published, originating from 761 different journals. The large number of sources indicates that ABSA research is widely distributed across various interdisciplinary journals.



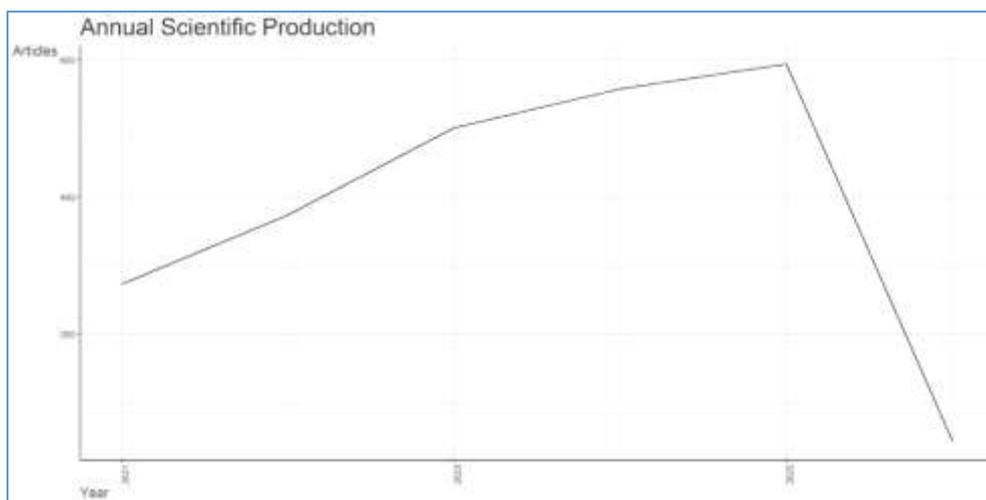
Figure 2 Bibliometric summary

The annual publication growth rate reached 30.58%, confirming that ABSA is a rapidly growing research field. This research involved 5,003 authors, with an average of 3.79 authors per article, reflecting the predominance of collaboration in ABSA research. In terms of content, 5,513 author keywords were recorded, reflecting the diversity of themes and approaches in ABSA research. The average document age of 2.59 years and the average citation rate per article of 12.5 indicate that ABSA publications are relatively recent and have a significant academic impact.

Furthermore, the international collaboration rate of 21.03% indicates cross-border collaboration, this relatively limited figure may stem from the language-specific nature of ABSA datasets, the concentration of research in technologically advanced countries with strong domestic networks, and disparities in funding and computational resources. Enhancing multilingual open datasets, cross-national grants, and shared research infrastructures could strengthen global collaboration and improve the methodological robustness and cross-cultural relevance of future ABSA studies.

### Number of Publications Per Year

Figure 3 displays the Annual Scientific Production (ASP) of ABSA-related publications from 2021 to early 2026. The trend line exhibits a consistent and steep upward trajectory, rising from 273 articles in 2021 to 594 articles in 2025. This growth pattern is not merely incremental it reflects the compounding effect of increasing researcher interest, expanded application domains, and the maturation of transformer-based architectures that made ABSA more tractable and impactful as a research area.



**Figure 3** Number of publications per year

More details regarding the number of related research publications (ABSA) per year can be seen in Table 2. Several factors explain this growth trajectory. First, the surge between 2022 and 2023 (from 374 to 501 articles, a 34% increase) coincides with the widespread adoption of pre-trained models such as BERT and RoBERTa in NLP tasks, which provided researchers with powerful baselines for ABSA experimentation. Second, the continued growth into 2024 and 2025 aligns with increasing application of ABSA to real-world domains including healthcare, e-commerce, and social media analysis, which broadened the pool of contributing disciplines beyond core NLP. Third, the apparent decline in 2026 (44 articles) should not be interpreted as a loss of momentum; the data collection cutoff was January 20, 2026, meaning the figure captures only the initial weeks of the year. Extrapolating from this partial data would project 2026 publications well above the 2025 figure.

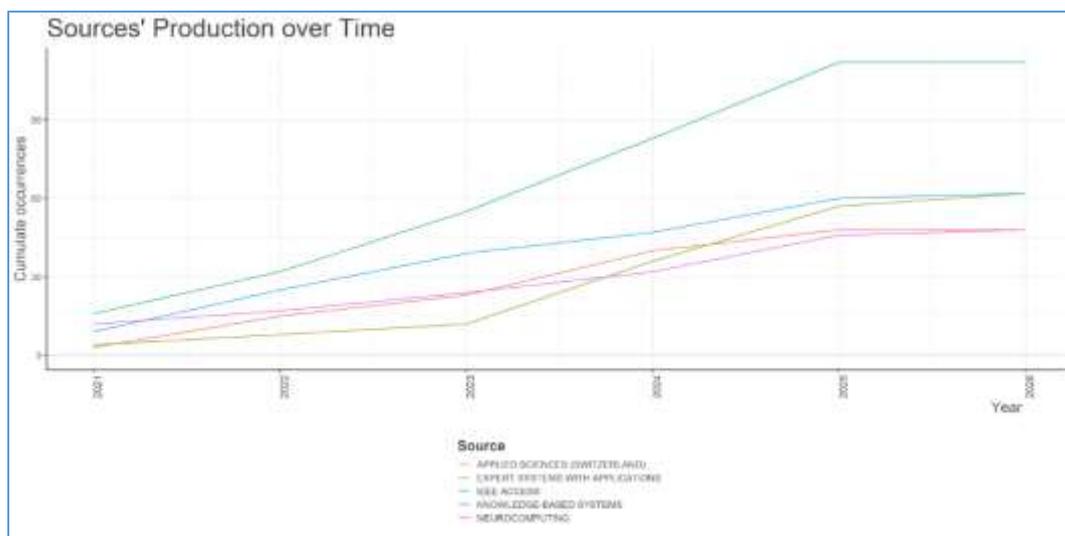
**Table 2** Number of publications per year

Year	Number of Articles
2021	273
2022	374
2023	501
2024	558
2025	594
2026	44

### Source's Production over Time

Figure 4 illustrates the cumulative publication growth across five leading journals in ABSA research: IEEE Access, Knowledge-Based Systems, Expert Systems with Applications, Applied Sciences (Switzerland), and Neurocomputing. The cumulative trajectory of each journal reveals not only volume but also the pace and consistency of scholarly engagement with ABSA topics.

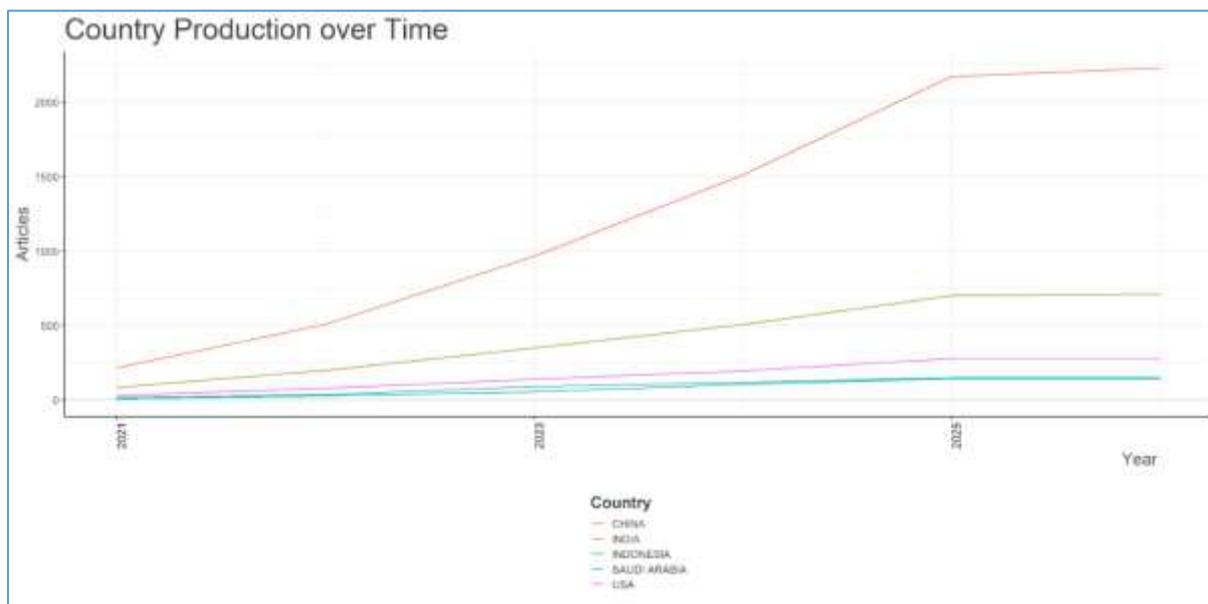
IEEE Access emerges as the most prolific publisher of ABSA-related research, attributed largely to its open-access policy, broad disciplinary scope, and rapid publication turnaround factors that attract applied AI researchers seeking wide dissemination. Its steep upward curve, particularly after 2022, reflects the journal's growing role as a venue for ABSA studies combining deep learning with real-world applications. The divergence in growth rates across journals is analytically significant, it suggests that different segments of the ABSA research community have developed distinct publication ecosystems based on methodological orientation. The concentration of ABSA publications in AI and data science journals rather than linguistics or social science venues also reveals that the field remains primarily driven by computational, rather than interpretive, research paradigms.



**Figure 4 Sources' production over time**

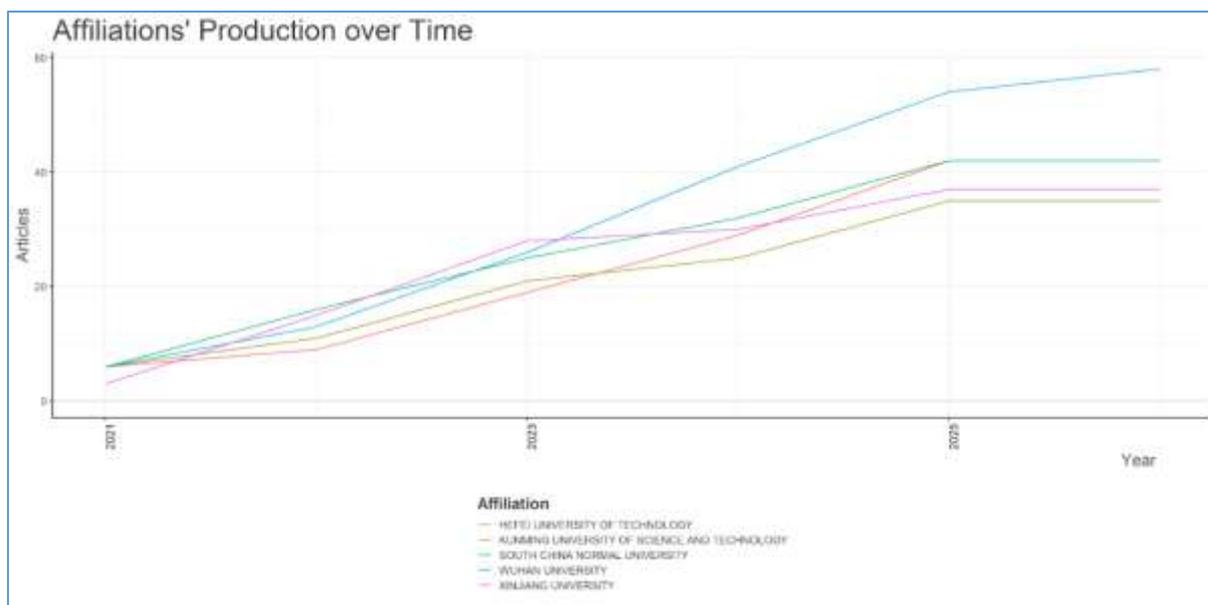
### Country Production over Time

Figure 5 maps the cumulative publication output by country from 2021 to 2026. China's dominance is unambiguous: its cumulative output by 2025 exceeds 2,000 articles, far outpacing all other nations. This concentration reflects China's strategic investment in AI research infrastructure, the large volume of postgraduate researchers producing NLP studies, and the availability of Chinese-language corpora that provide a natural testbed for multilingual ABSA models. India occupies a strong second position with consistent annual growth, driven by expanding university research programs and a large software engineering workforce that bridges academic and applied NLP.



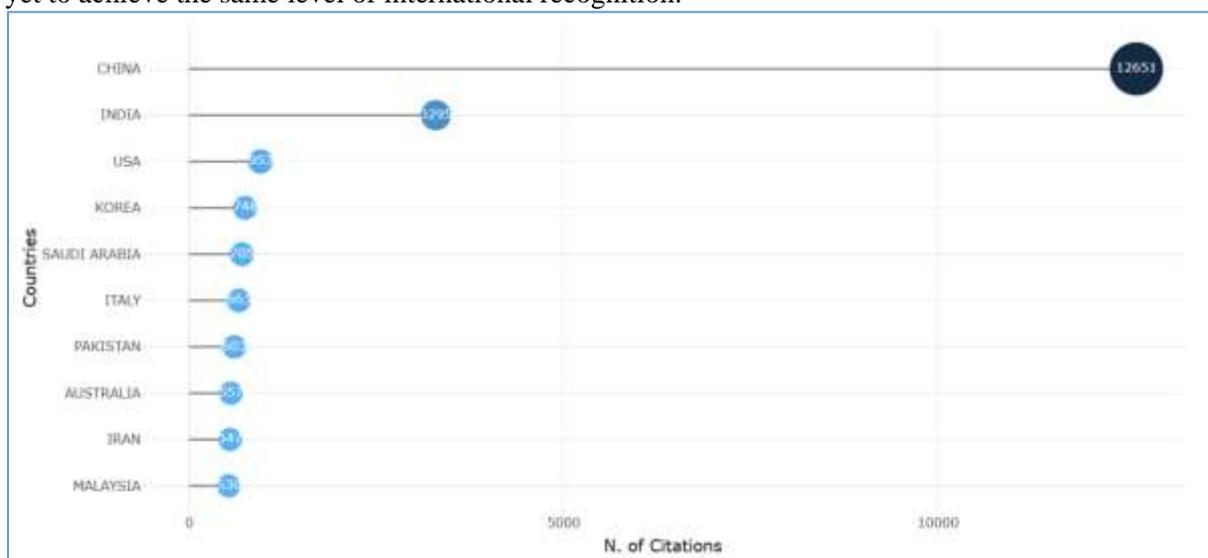
**Figure 5 Country production over time**

The graph in Figure 6 shows a consistent increase in the number of publications from all institutions analyzed. Wuhan University appears to be the most dominant, with the highest growth, followed by South China Normal University and Hefei University of Technology, demonstrating stable and sustained research contributions. Meanwhile, Kunming University of Science and Technology and Xinjiang University also experienced gradual increases, indicating the institutions' expanding involvement in this research field.



**Figure 6 Affiliations' production over time**

Figure 7 depicts citation counts by country. China's 12,651 citations are more than ten times those of India (1,265), indicating not only greater volume but also significantly higher citation impact per published article. This implies that Chinese ABSA research is not simply producing more papers, it is producing highly cited works that are shaping the direction of the field globally. The United States, Korea, and Saudi Arabia occupy the mid-tier, reflecting influence that extends beyond their raw publication counts. Countries such as Malaysia, Iran, Australia, and Pakistan have low citation counts despite active publication, suggesting that their contributions, while growing in volume, have yet to achieve the same level of international recognition.



**Figure 7 Most cited countries**

### Keyword Co-occurrence Analysis

Figure 8 presents the keyword co-occurrence network, which maps the intellectual structure of ABSA research by visualizing how frequently author-assigned keywords appear together across articles. Three distinct research clusters emerge from this analysis, each representing a coherent community of practice.

The blue cluster (left) is the most technically specific, organized around keywords such as 'aspect-based sentiment analysis,' 'graph attention networks,' 'dependency trees,' 'contrastive learning,' and 'multi-task learning.' This cluster represents the algorithmic core of ABSA research, where

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scholars focus on improving model architecture and capturing syntactic-semantic relationships. The density of connections within this cluster suggests a tight-knit research community sharing methodological foundations and frequently citing one another.

The red cluster (right) represents the broader NLP and machine learning mainstream, with keywords including 'sentiment analysis,' 'deep learning,' 'neural networks,' 'machine learning,' 'text mining,' and domain-specific applications such as 'social media,' 'online reviews,' and 'COVID-19.' This cluster is characterized by higher centrality—meaning that its core terms ('sentiment analysis') serve as hubs connecting a wide variety of research streams. It represents applied ABSA research adapted to specific real-world problems, where the methodological contribution is secondary to the application context.

The smaller green cluster (bottom center) occupies a bridging role, containing keywords such as 'sentiment classification,' 'aspect extraction,' 'word embedding,' and 'convolutional neural networks.' These are foundational techniques that predate the transformer era and continue to appear in comparative studies, baseline evaluations, and resource-constrained settings. Its bridging position between the blue and red clusters indicates that foundational ABSA methods continue to serve as reference points even as the field advances.

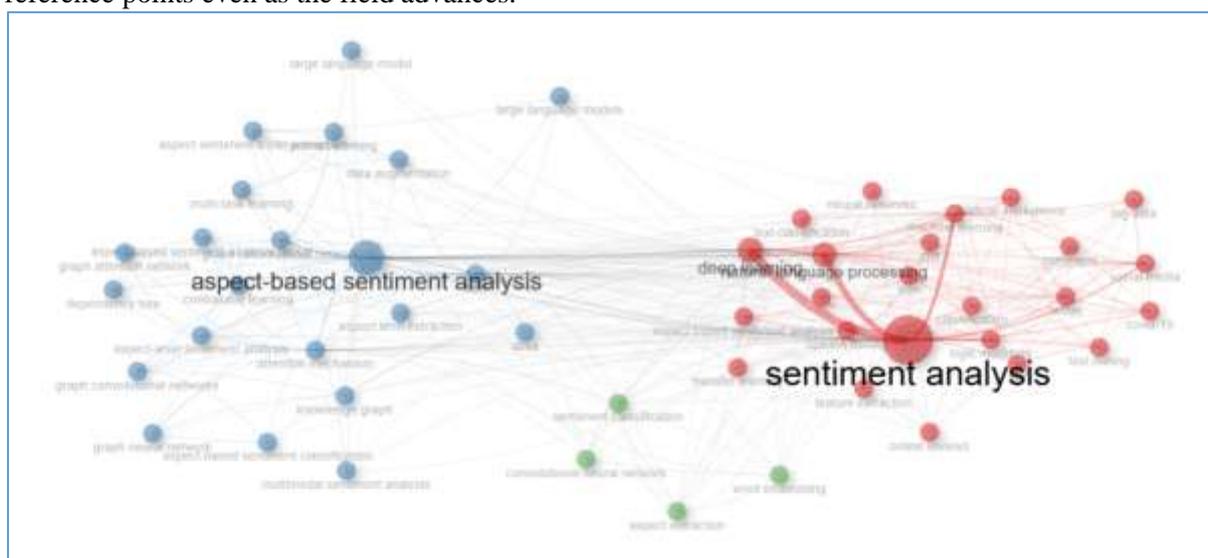


Figure 8 Co-occurrence network

### Thematic Mapping and Evolution of Research Themes

The graph in Figure 9 shows a map of the position of ABSA's research themes based on two criteria: centrality (X-axis), which indicates how important the theme is in connecting various research topics, and density (Y-axis), which indicates how mature and developed the theme is. This diagram is divided into four quadrants with different interpretations.

Motor Themes (upper right quadrant) represent topics that are both highly developed internally and highly connected to the broader field. In this map, the cluster containing 'aspect-based sentiment analysis,' 'BERT,' and 'attention mechanisms' is positioned in the upper half of the quadrant (high density), indicating that these techniques have achieved a high level of technical maturity and are functioning as the primary engine of ABSA research. This finding confirms that transformer-based ABSA is no longer an emerging topic, it has become the dominant paradigm around which the field organizes itself. The proximity of BERT and attention mechanisms within this cluster signals their co-evolution: attention mechanisms were initially a standalone contribution, but have become inseparable from the BERT-based ABSA research tradition.

Basic Themes (lower right quadrant) include 'sentiment analysis,' 'natural language processing,' 'machine learning,' 'deep learning,' and 'aspect extraction.' These themes are highly central, meaning they connect to a wide range of research topics, but have lower internal density, suggesting they serve more as broad scaffolding than as specialized research frontiers. Their position reflects their foundational status: they underpin ABSA without being uniquely defined by it. Researchers working in these areas are simultaneously contributing to ABSA and to adjacent NLP domains.

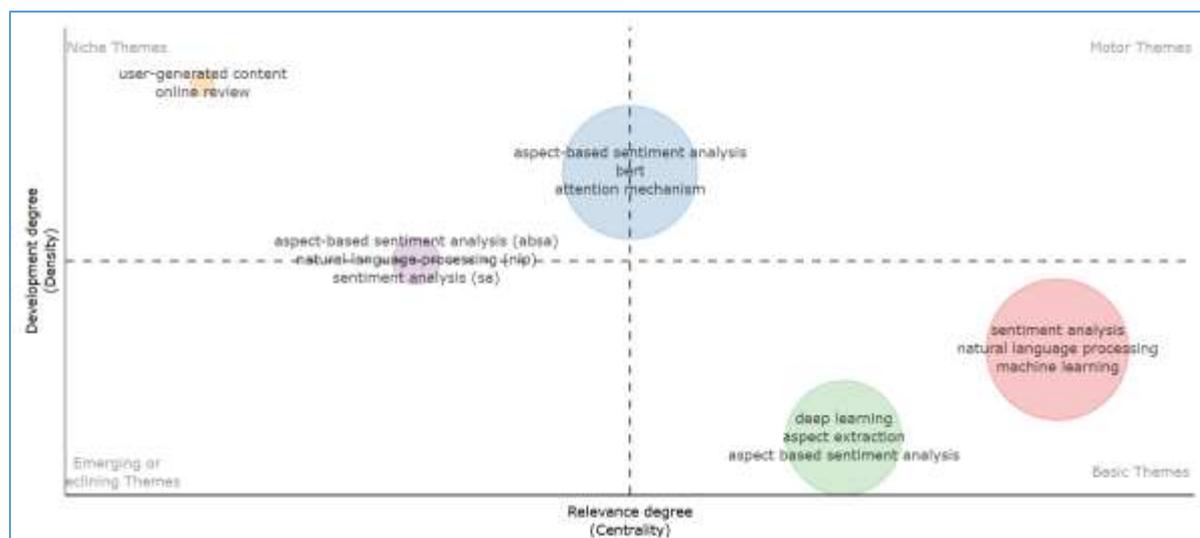


Figure 9 Thematic map

Niche Themes (upper left quadrant) include 'user-generated content' and 'online reviews' topics that are highly specialized and internally developed but weakly connected to the broader field. This placement suggests that ABSA research applied to online consumer reviews has evolved into a self-contained literature with its own methodological conventions and datasets, but with limited methodological exchange with the algorithmic core. This insularity may limit the transferability of findings to other application domains.

Emerging or Declining Themes (lower left quadrant) contain clusters represented by ABSA abbreviations such as 'absa,' 'nlp,' and 'sa.' Their weak centrality and density suggest either that researchers using these shorthand terms are working in less interconnected subgroups, or that abbreviated keyword usage is analytically less informative than full-term usage in co-occurrence analysis. This finding has a practical implication for indexing: authors should prefer full terminology over abbreviations to maximize keyword discoverability and citation linkage.

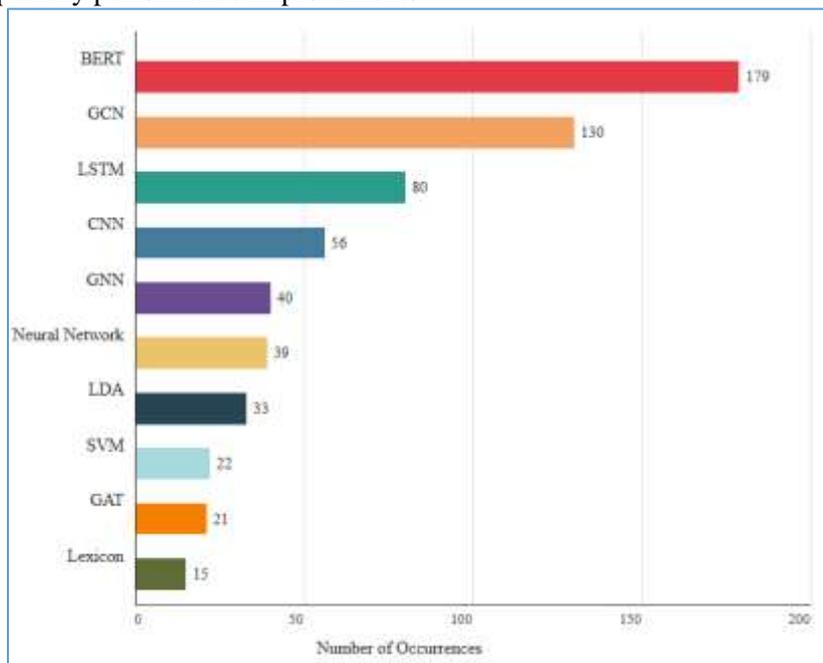
Figure 10 presents a thematic evolution map that contrasts the distribution of research themes across two time windows: 2021–2024 and 2025–2026. This Sankey-style visualization reveals how research attention has shifted between periods by showing how thematic streams grow, shrink, or migrate. The most analytically significant finding is the rise of 'online public opinion' as a dominant theme in 2025–2026, absorbing much of the research bandwidth previously occupied by 'aspect-based sentiment analysis' in 2021–2024. This shift indicates a disciplinary reorientation: ABSA is being increasingly deployed not just as a technical text classification tool, but as an instrument for understanding collective public sentiment at scale. This transition is consistent with broader societal trends, including the growing importance of social media monitoring for policymaking, brand management, and public health surveillance. Meanwhile, themes such as 'deep learning' and 'sentiment analysis' remain stable across both periods, confirming their status as enduring foundational concerns. The emergence of 'graph neural networks' and 'online reviews' as distinct themes in 2025–2026 signals two parallel developments: a methodological frontier (GNNs enabling richer relational modeling) and an application frontier (review analysis becoming more structured and domain-specific).



**Figure 10 Thematic evolution**

### Frequency of Model Use

BERT's dominance is explained by its pre-trained bidirectional contextual representations, which are uniquely suited to ABSA's core challenge: disambiguating the sentiment polarity of aspect terms based on their surrounding context. GCN's second-place position reflects its complementary strengths—where BERT captures sequential contextual semantics, GCN captures syntactic dependency structure through graph-based encoding of parse trees. The joint use of BERT and GCN in many studies explains their co-dominance and the emergence of hybrid architectures as a defining feature of state-of-the-art ABSA. LSTM and CNN, while outperformed by transformer-based models, retain relevance in scenarios where computational resources are limited or when sequential and local feature extraction are sufficient. The persistence of LDA and SVM in the corpus is best understood as a methodological baseline: recent studies regularly compare advanced models against these classical approaches to quantify performance improvements.



**Figure 11 Frequency of model use**

Figure 12 provides a time-series view of model usage frequency per year, revealing the dynamic evolution of the ABSA methodological landscape. The most structurally important finding is the sharp rise of Large Language Models (LLMs) beginning in 2023, which represents a potentially disruptive shift in the field's trajectory. Unlike BERT (a task-specific fine-tuned encoder) and GCN (a graph-based encoder for structured syntax), LLMs such as GPT-4 introduce few-shot and zero-shot

capabilities that fundamentally challenge the assumption that ABSA requires large labeled training datasets. Their ascent from near-zero mentions in 2021 to peak representation in 2025 mirrors the broader 'ChatGPT moment' that transformed NLP research globally from late 2022 onward.

The concurrent rise of GNN usage alongside LLMs is analytically significant: it suggests that the field is pursuing two parallel but potentially convergent research directions—one leveraging the generative and few-shot capabilities of large language models, and the other exploiting the structural reasoning capabilities of graph neural networks. The steep decline across all models in 2026 is an artifact of the data collection timeline (cutoff: January 20, 2026) and should not be interpreted as a reversal of these trends. Based on the trajectory of LLM adoption and the continued maturation of graph-based ABSA, future research is expected to increasingly integrate both paradigms—with LLMs providing flexible semantic understanding and GNNs providing structured relational reasoning over aspect-opinion dependencies.

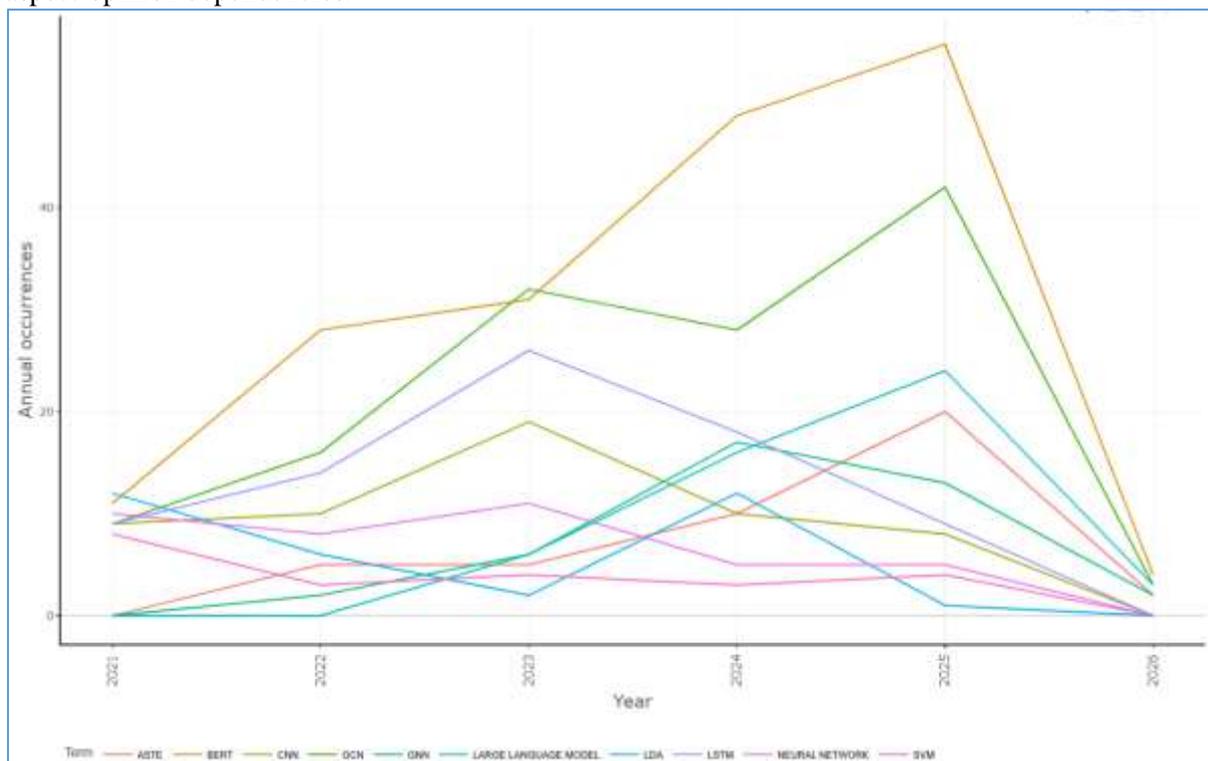


Figure 12 Frequency of model use per year

## 5 Conclusion

This study systematically answers the research objectives by applying six bibliometric analysis techniques to map the development of Aspect-Based Sentiment Analysis (ABSA) from 2021 to 2025. First, the analysis of the number of publications per year confirms a consistent and significant growth trend, indicating that ABSA is an expanding and dynamic research field. Second, the examination of source production over time identifies leading journals such as IEEE Access, Knowledge-Based Systems, and Expert Systems with Applications as dominant publication venues. Third, country production analysis reveals a strong concentration of research output and citation impact in Asian countries, particularly China and India, with Chinese institutions emerging as major research centers. Fourth, keyword co-occurrence analysis demonstrates that ABSA maintains a distinct methodological identity while remaining strongly connected to broader sentiment analysis and deep learning research. Fifth, thematic mapping and thematic evolution analyses confirm the maturity of transformer-based approaches as motor themes and highlight a recent shift toward online public opinion analysis and graph-based modeling. Finally, the frequency of model use clearly shows the dominance of BERT and GCN architectures, alongside the rapid rise of Large Language Models (LLMs), replacing classical machine learning methods. Collectively, these findings provide a comprehensive and structured understanding of research trends and algorithmic evolution in ABSA research.

This research remains limited to a single database and a quantitative bibliometric approach. Therefore, further research is suggested to integrate bibliometric analysis with systematic literature review, expand data sources, and explore the application of ABSA that combines large language models, cross-language approaches, and multimodal data. The findings of this study are expected to serve as a strategic reference for researchers in understanding the current ABSA research landscape and formulating further research directions.

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