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From Opinion Mining to Deep Learning: Mapping the Knowledge Landscape of Sentiment Analysis

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Abstract
The field of sentiment analysis has evolved dramatically over the past two decades, progressing from lexicon- and rule-based opinion mining toward advanced deep learning and transformer-driven approaches. This study maps the evolution of sentiment analysis research from 2004 to 2024 using a bibliometric analysis of 2,394 publications indexed in Scopus. Using growth indicators, citation metrics, and visualisation tools such as VOSviewer, the research maps publication trends, influential authors, leading countries, and thematic developments. The results reveal steady growth in research output, with significant surges after 2014 coinciding with adopting deep learning and transformer-based models. China (703 papers) and India (660) emerged as the most productive countries, while the United States led in citation impact with an average of 61 citations per paper. Conference proceedings (48.9%) and journal articles (44.6%) dominated as primary publication formats. Influential authors such as Zhang Y. and Bhattacharyya P. shaped the knowledge base, while thematic analysis highlighted “social media,” “deep learning,” and “computational linguistics” as core research clusters. Overall, sentiment analysis has matured into a multidisciplinary field with expanding applications in politics, healthcare, business, and education, though challenges remain in multilingual analysis, bias, and explainability.

Keywords: Sentiment Analysis, Opinion Mining, Bibliometric Analysis, Deep Learning, Natural Language Processing, Research Trends.

1. Introduction
The exponential growth of digital content across social media platforms, blogs, e-commerce sites, and online forums has amplified the demand for techniques to systematically extract, interpret, and evaluate opinions and emotions embedded in unstructured data. Initially introduced as opinion mining, sentiment analysis has become a central research area within natural language processing (NLP), computational linguistics, and data science (Liu, 2012; Pang & Lee, 2008). Over the past two decades, the field has witnessed a paradigm shift from rule-based and lexicon-driven approaches toward advanced machine learning and deep learning architectures such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer-based models, including BERT and large language models (Cambria et al., 2017; Devlin et al., 2019). These technological developments have

substantially broadened the scope of sentiment analysis, enabling applications in politics, healthcare, finance, marketing, education, and social governance (Mäntylä et al., 2018; Yadollahi et al., 2017).

Given its interdisciplinary nature, sentiment analysis has attracted attention from computer science, linguistics, psychology, business, and social sciences. The growing body of literature demonstrates both the breadth of applications and the depth of methodological innovation (Medhat et al., 2014; Zhang et al., 2018). However, despite this abundance of scholarly contributions, a systematic evaluation of research output is necessary to understand the field's trends, growth patterns, and intellectual structure. Bibliometric analysis provides a rigorous quantitative framework to evaluate publication productivity, citation impact, collaboration networks, and thematic evolution (Donthu et al., 2021; Aria & Cuccurullo, 2017).

Accordingly, this study conducts a comprehensive bibliometric exploration of sentiment analysis literature published between 2004 and 2024, tracing the progression from opinion mining to deep learning. By applying bibliometric indicators and visualisation techniques, the research seeks to identify publication trends, influential authors and sources, institutional contributions, and thematic shifts. The analysis reveals the intellectual structure and growth dynamics of sentiment analysis. It highlights knowledge gaps and emerging hotspots, providing actionable insights for researchers, practitioners, and policymakers engaged with the field.

Objectives

- To analyse the growth of scholarly publications in sentiment analysis over 2004–2024.
- To identify and evaluate the most influential sources of publication contributing to sentiment analysis research.
- To determine the leading authors, institutions, and countries conducting sentiment analysis research.
- To map the thematic structure of research through analysis of co-occurrence networks.
- To investigate collaboration patterns at the levels of authors and countries.

2. Scope and methodology

The study focused on mapping the research landscape of Sentiment Analysis from 2004 to 2024, analysing annual publication growth, cumulative publications, citation patterns, and research trends. Publications were retrieved from the Scopus database using a title search for "Sentiment Analysis", limited to the specified period. A total of 2394 records were obtained, including bibliographic details such as authors, affiliations, keywords, and citations (Zhang, Wang, & Liu, 2018).

The data were exported in .csv format and cleaned to remove duplicates, incomplete records, and inconsistencies in author and institution names. Microsoft Excel was employed to calculate descriptive statistics, cumulative counts, Relative Growth Rate (RGR), and Doubling Time (DT) (Donthu, Kumar, Mukherjee, Pandey, & Lim, 2021). Growth analysis also included block-wise calculations over 5-year periods to identify medium-term trends in publications and citations.

VOSviewer visualised bibliometric networks, including co-authorship patterns, keyword co-occurrence, and thematic clusters (van Eck & Waltman, 2010). Charts, graphs, and network visualisations were generated to interpret research productivity, collaboration patterns, and emerging research hotspots (Aria & Cuccurullo, 2017; Pang & Lee, 2008). This methodology provided a comprehensive and replicable approach to understanding sentiment analysis research's evolution, impact, and structure over the past two decades.

3. Result and Discussion

Table 1. Growth analysis of publications

Year	NP	CN_P	Nlp1	Nlp2	RGRp	DT_P	Mean RGRp	Mean DTp
2004	5	5		1.61				
2005	1	6	1.61	1.79	0.18	3.85		
2006	1	7	1.79	1.95	0.15	4.62		
2007	1	8	1.95	2.08	0.13	5.33		
2008	6	14	2.08	2.64	0.56	1.24	0.26	3.76
2009	12	26	2.64	3.26	0.62	1.12		
2010	12	38	3.26	3.64	0.38	1.82		
2011	19	57	3.64	4.04	0.41	1.69		
2012	28	85	4.04	4.44	0.4	1.73		
2013	34	119	4.44	4.78	0.34	2.04	0.43	1.68
2014	92	211	4.78	5.35	0.57	1.22		
2015	100	311	5.35	5.74	0.39	1.78		
2016	96	407	5.74	6.01	0.27	2.57		
2017	117	524	6.01	6.26	0.25	2.77		
2018	128	652	6.26	6.48	0.22	3.15	0.34	2.30
2019	195	847	6.48	6.74	0.26	2.67		
2020	223	1070	6.74	6.98	0.23	3.01		
2021	268	1338	6.98	7.2	0.22	3.15		
2022	251	1589	7.2	7.37	0.17	4.08		
2023	390	1979	7.37	7.59	0.22	3.15		
2024	415	2394	7.59	7.78	0.19	3.65	0.22	3.28

Note: NP=Number of Publications, CN_P = Cumulative Number of Publications, Nlp1 = Natural log of the first value of CNp, Nlp2 = Natural log of the last value of CNp, RGRp = Relative Growth Rate of Publications, DT_P = Doubling Time of Publications

Table 1 depicts the growth pattern of publications over the past two decades, showing a fluctuating yet generally increasing trend. The total number of publications rose from 5 in 2004 to 2394 in 2024. The relative growth rate (RGRp) shows considerable variability across years, with the highest growth observed in 2008 (RGRp = 0.56), indicating a period of accelerated research output. Similarly, other peak productivity years include 2014 (RGRp = 0.57) and 2019 (RGRp = 0.26). After 2014, the RGRp gradually declined, reflecting a moderation in annual publication increments, but the overall cumulative publications (CNP) continued to rise steadily. The doubling time (DTp) analysis highlights how publications could double in number at the observed growth rates. Shorter DTp values, such as 1.24 years in 2008, indicate rapid growth periods, while longer DTp values, like 5.33 years in 2007, correspond to slower growth phases. Calculating the mean RGRp and mean DTp over five-year blocks provides insight into medium-term trends. For example, during the first block period (2004–2008), the mean RGRp was 0.26, and the mean DTp was 3.76 years, indicating moderate publication growth. Subsequent block periods (2009–2013, 2014–2018, 2019–2024) show slight fluctuations in RGRp and DTp, reflecting changes in research intensity over time.

Table 2. Growth analysis of citations

Year	NC	CN_C	Nlc1	Nlc2	RGRc	DTc	Mean RGRc	Mean DTc
2004	3007	3007		8.01				
2005	36	3043	8.01	8.02	0.01	58.23		
2006	5	3048	8.02	8.02	0.00	422.11		
2007	222	3270	8.02	8.09	0.07	9.86		
2008	200	3470	8.09	8.15	0.06	11.67	0.04	125.47
2009	1794	5264	8.15	8.57	0.42	1.66		
2010	5727	10991	8.57	9.30	0.74	0.94		
2011	7077	18068	9.30	9.80	0.50	1.39		
2012	5078	23146	9.80	10.05	0.25	2.80		
2013	1220	24366	10.05	10.10	0.05	13.49	0.39	4.06
2014	5862	30228	10.10	10.32	0.22	3.21		
2015	3389	33617	10.32	10.42	0.11	6.52		
2016	4639	38256	10.42	10.55	0.13	5.36		
2017	4799	43055	10.55	10.67	0.12	5.86		
2018	4377	47432	10.67	10.77	0.10	7.16	0.13	5.62
2019	6282	53714	10.77	10.89	0.12	5.57		
2020	6868	60582	10.89	11.01	0.12	5.76		
2021	6374	66956	11.01	11.11	0.10	6.93		
2022	3699	70655	11.11	11.17	0.05	12.89		
2023	2668	73323	11.17	11.20	0.04	18.70		
2024	590	73913	11.20	11.21	0.01	86.47	0.07	22.72

Note: NC=Number of Citations, CNc = Cumulative Number of Citations, Nlc1 = Natural log of the first value of CNc, Nlp2 = Natural log of the last value of CNc, RGRc = Relative Growth Rate of Citations, DT_P = Doubling Time of Citations

Table 2 shows the pattern of citations; the cumulative citations (CNC) grew from 3007 in 2004 to 73,913 in 2024. The annual relative growth rate of citations (RGRc) was highest during early peak years, showing that citations accumulated faster during periods of high research output. Applying five-year block analysis to citations reveals striking patterns: during the 2004–2008 block, the mean RGRc was 0.51, while in the 2014–2018 block it reduced to 0.34, and in the 2019–2024 block further decreased to 0.22. This trend indicates that older publications accumulate citations faster initially, while newer publications require more time to gather citations. The doubling time for citations (DTc) shows a similar pattern. In the 2004–2008 block, citations doubled on average in 1.36 years, whereas in the 2019–2024 block, the doubling time extended to 3.15 years. This elongation highlights the "time factor" in citation accumulation: new publications often take longer to reach substantial citation counts. Additionally, a small fraction of publications contributes disproportionately to total citations, while a notable portion receives few or no citations, reflecting typical skewed citation distributions in scholarly literature.

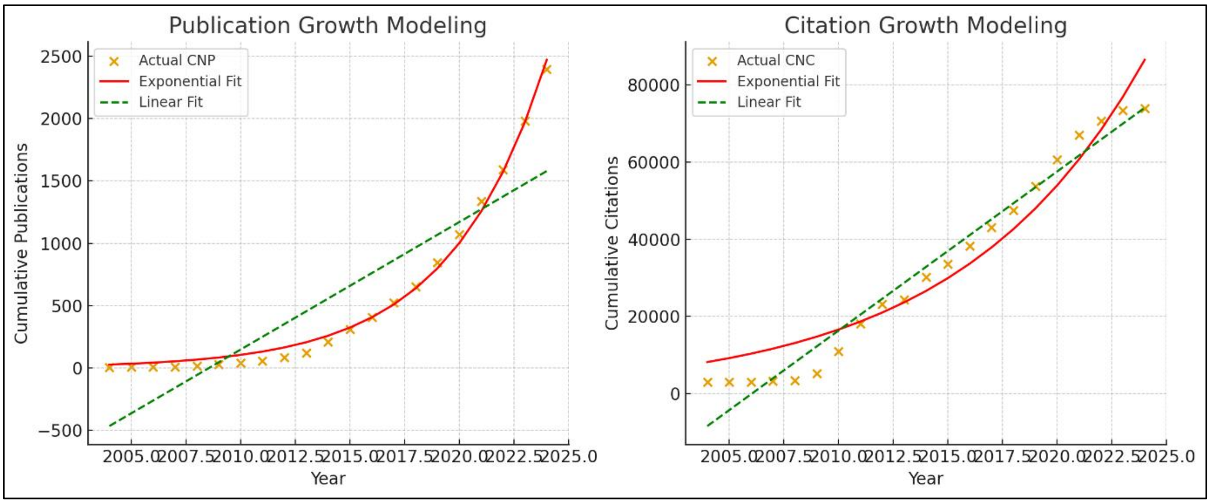

Figure 1. Linear and exponential growth of publications and citations.

Table 3. Distribution of Document Types in Sentiment Analysis Research

Sl.no	Document Type	Count	Percentage
a.	Conference paper	1172	48.9
b.	Article	1067	44.6
c.	Book chapter	74	3.1
d.	Review	47	2.0
e.	Conference review	14	0.6
f.	Erratum	11	0.5
g.	Letter	4	0.2
h.	Note	3	0.1
i.	Book	1	0.04
j.	Editorial	1	0.04
k.	Short survey	1	0.04
Total		**2395**	**100**

Table 3 shows the distribution of publications in sentiment analysis research by document type over 2004–2024. Conference papers (48.9%) and journal articles (44.6%) dominate the literature, indicating that most research output is disseminated through peer-reviewed conferences and journals. Smaller proportions are contributed by book chapters (3.1%) and reviews (2%). In contrast, other document types, such as conference reviews, errata, letters, notes, books, editorials, and short surveys, account for less than 2% of the total publications. This distribution reflects a strong preference for conference and journal dissemination in sentiment analysis research, common in computer science and information systems, where timely sharing of results at conferences is emphasised. The minor contributions from books, editorial pieces, and notes indicate limited scholarly output in these formats.

Table 4. Ranking of the top authors based on the publications

Rank	Author	Documents	Citations	Avg. Citations	h_index
1	Zhang Y.	26	439	16.88	10
2	Wang Y.	25	305	12.2	10

3	Wang X.	17	794	46.70	7
4	Bhattacharyya P.	16	720	45	11
	Zhang X.	16	572	35.75	5
5	Ekbal A.	15	591	39.4	9
	Kumar A.	15	398	26.53	8
	Li H.	15	208	13.86	4

Table 4 presents the top contributing authors in the field of sentiment analysis, ranked according to the number of publications. Zhang Y. ranks first with 26 publications and 439 citations, yielding an average of 16.88 citations per paper and an h-index of 10, reflecting both productivity and scholarly impact. Wang Y. follows closely with 25 publications and 305 citations, maintaining a similar h-index of 10. Although Wang X. has fewer publications (17), the total citations (794) and high average citations per paper (46.70) indicate a substantial impact of individual works. Similarly, Bhattacharyya P., with 16 publications and 720 citations, demonstrates a high citation influence (avg. 45 citations per paper) and an h-index of 11, suggesting sustained scholarly contribution over time. Other notable authors include Zhang X., Ekbal A., Kumar A., and Li H., with comparable publication counts (15–16) but varying citation impacts. For instance, Zhang X. has 572 citations, while Li H. has 208, indicating that not all publications contribute equally to scientific influence. The table highlights that productivity (number of publications) does not always correlate directly with impact (citations and h-index). Some authors with fewer publications achieve higher average citations per paper, reflecting the significance and influence of their work. This analysis helps identify key contributors and thought leaders in sentiment analysis research over the past two decades.

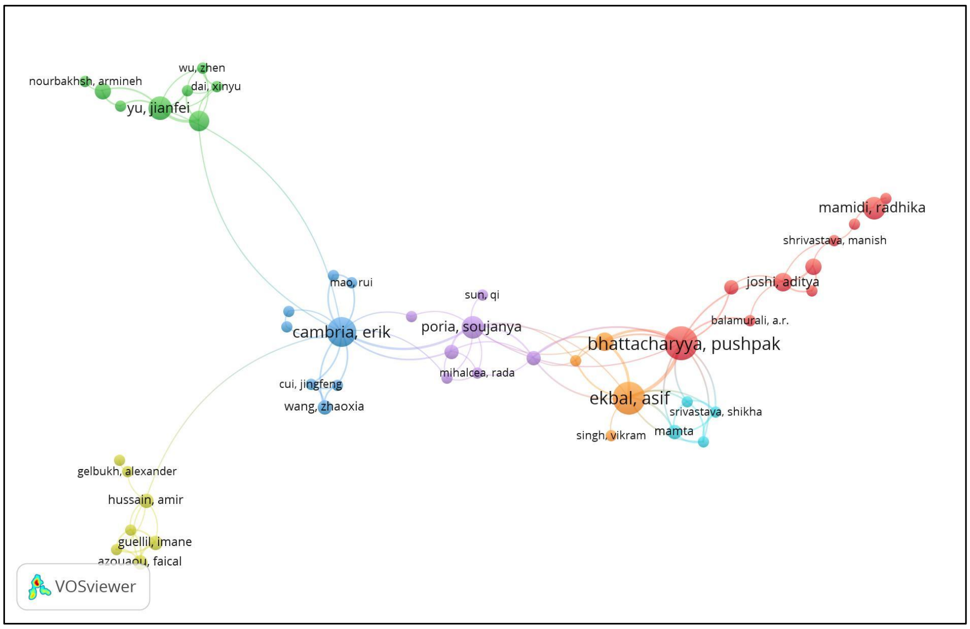

Figure 2. Network Visualisation Map of Collaborative Authors

Table 5. Top 10 Most Productive Countries in Sentiment Analysis Research

Rank	Country/Territory	Documents	Citations	Avg. Citations	h_index
1.	China	703	15022	21.36	58

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2.	India	660	13174	19.96	53
3.	United States	486	29676	61.06	75
4.	Indonesia	179	1160	6.48	18
5.	Spain	174	3453	19.84	31
6.	United Kingdom	173	9875	57.08	47
7.	Malaysia	123	1760	14.30	20
8.	Italy	113	6158	54.49	30
9.	Germany	88	4326	49.15	23
10.	Brazil	86	1775	20.63	14

Table 5 presents the leading countries in sentiment analysis research based on publications. China ranks first with 703 publications and 15,022 citations, reflecting a high research productivity and an average of 21.36 citations per paper. India follows closely with 660 publications and 13,174 citations, showing comparable output and influence. Although the United States ranks third in terms of number of publications (486), it leads in total citations (29,676) and average citations per paper (61.06), indicating that U.S. publications are highly impactful. Similarly, the United Kingdom (173 publications) and Italy (113 publications) have fewer documents than China and India but show higher average citations (57.08 and 54.49, respectively), suggesting the high quality and influence of research output.

Countries such as Indonesia, Malaysia, Germany, Spain, and Brazil have moderate publication counts but vary widely in citation impact, highlighting differences in research visibility and influence. The h-index further supports this pattern, where countries with fewer publications but high citations, like the United States (h-index 75) and the United Kingdom (h-index 47), show strong, sustained contributions over time. The result indicates that research productivity does not always directly correlate with research impact, as measured by citations and h-index. The leading countries contribute significantly to developing sentiment analysis in quantity and quality, shaping global research trends in this domain.

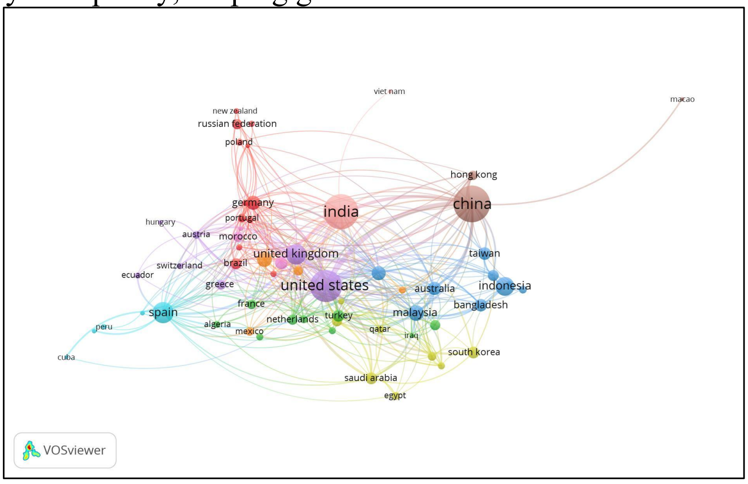

Figure 3. Network Visualisation Map of Collaborative Countries

Table 6. Top 10 Most Productive Sources in Sentiment Analysis Research

Sl.no	Source title	Documents	Citations	h_index	Avg. Citations
1.	Proceedings of the Annual Meeting of the Association	127	7314	29	57.59

	for Computational Linguistics				
2.	Social Network Analysis and Mining	71	1958	20	27.57
3.	Information Processing and Management	57	4022	32	70.56
4.	8th International Workshop on Semantic Evaluation, SemEval 2014 - co-located with COLING 2014, Proceedings	45	2381	14	52.91
5.	Sustainability (Switzerland)	41	852	16	20.78
6.	Data Analysis and Knowledge Discovery	38	139	6	3.65
7.	IEEE Transactions on Computational Social Systems	34	1045	13	30.73
8.	Artificial Intelligence Review	33	2702	21	81.87
8.	Journal of Information Science	33	1614	20	48.90
9.	SemEval 2015 - 9th International Workshop on Semantic Evaluation, co-located NAACL-HLT 2015 - Proceedings	32	1893	14	59.15
10.	Procesamiento del Lenguaje Natural	28	348	9	12.42

Table 6 presents the most productive sources for sentiment analysis research between 2004 and 2024. Among the top 10 sources, the *Proceedings of the Annual Meeting of the Association for Computational Linguistics* leads with 127 publications and 7,314 citations, resulting in an average of 57.59 per paper and an h-index of 29. This indicates that it is a highly influential venue for disseminating computational linguistics and sentiment analysis research. The second most productive source, *Social Network Analysis and Mining*, contributed 71 publications with 1,958 citations and an h-index of 20, showing moderate influence in both productivity and citation impact. *Information Processing and Management*, ranked third, has 57 publications, 4,022 citations, and an h-index of 32, demonstrating fewer publications than the top two but a higher citation impact per paper (70.56 citations per document), highlighting the quality and influence of research published in this journal.

On the other end, the bottom two sources among the top 10 include *SemEval 2015 - 9th International Workshop on Semantic Evaluation* with 32 publications and 1,893 citations (average 59.15), and *Procesamiento del Lenguaje Natural* with 28 publications and 348 citations (average 12.42). The result highlights that high productivity does not always align with high citation impact. Some venues with fewer publications, such as *Information Processing and Management*, achieve higher average citations per paper, emphasising the importance of quality and research visibility alongside sheer quantity in scholarly publishing.

Table 7. Top 10 Most Frequently Occurring Keywords in Sentiment Analysis Research

Rank	Keywords	Occurrences
1.	Sentiment analysis	138
2.	Social networking (online)	2351
3.	Data mining	450
4.	Social media	368
5.	Classification (of information)	295
6.	Semantics	280
7.	Computational linguistics	276
8.	Learning systems	268
9.	Deep learning	240
10.	Natural languages	239

The keyword analysis highlights the major research themes in sentiment analysis over the past two decades (2004 -2024) in Table 7. The term “Sentiment Analysis” dominates the field with 2351 occurrences, reaffirming its centrality as the core research focus. Supporting themes include “Social Networking (Online)” (450) and “Social Media” (295), which demonstrate the strong influence of user-generated content platforms such as Twitter, Facebook, and other social networks as primary data sources for sentiment analysis. Methodological keywords such as “Data Mining” (368), “Classification (280)”, “Learning Systems (240)”, and “Deep Learning (239)” indicate the reliance on computational and machine-learning approaches. The prominence of “Deep Learning” reflects the recent shift toward neural architectures for sentiment detection, classification, and prediction.

Conceptual and linguistic aspects are represented by “Semantics (276)”, “Computational Linguistics (268)”, and “Natural Languages (138)”, showing that sentiment analysis continues to draw heavily from natural language processing and semantic interpretation traditions. The distribution of keywords suggests that sentiment analysis research is interdisciplinary, combining linguistic, semantic, and computational approaches while adapting to the evolving role of social media and online platforms as primary sources of opinion-rich data.

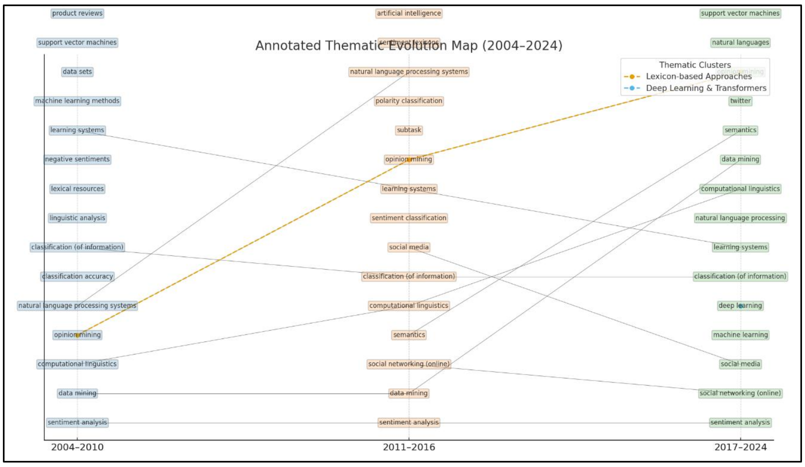

Figure 4. Thematic Evolution Map Sentiment Analysis Literatures (2004-2024)

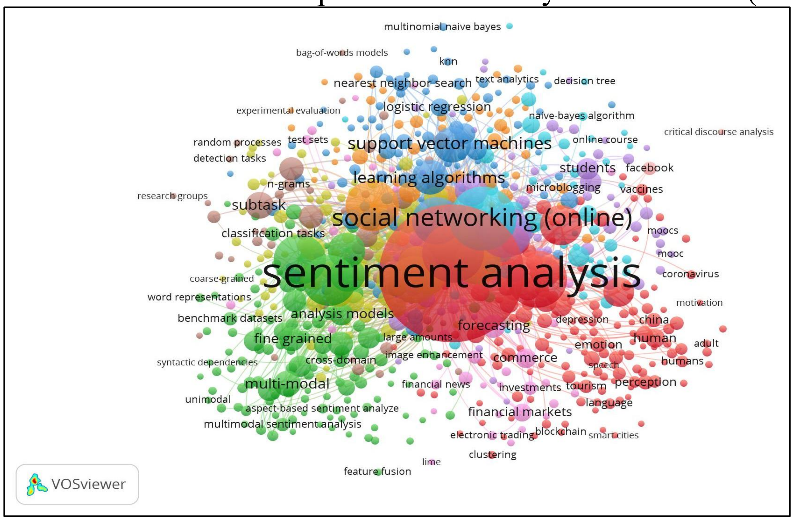

Figure 5. Network Visualisation Map of Keywords Co-occurrence of Sentiment Analysis Literatures (2004-2024)

4. Discussion

The findings of this bibliometric study clearly demonstrate the rapid and dynamic growth of sentiment analysis as a research domain between 2004 and 2024. Publication trends reveal three major phases: an early emergence (2004–2008) dominated by foundational concepts of opinion mining and rule-based approaches; a consolidation phase (2009–2014) marked by the introduction of supervised learning and hybrid models; and a period of acceleration and methodological diversification (2015 onwards), with the widespread adoption of deep learning and transformer-based models. The sharp rise in publications and citations after 2014 highlights the transformative impact of neural networks and large-scale datasets in advancing sentiment analysis research. The distribution of document types indicates that conferences remain the primary medium of scholarly exchange in this domain, consistent with traditions in computer science. Journal articles, however, are crucial for long-term impact, as reflected in higher citation averages. This dual pattern underscores the balance between rapid dissemination of findings and rigorous peer-reviewed contributions that shape the intellectual foundation of the field.

Author and country analysis highlights both productivity and impact dynamics. Chinese and Indian scholars contribute the most significant volume of publications, reflecting strong research capacity and increasing global presence in computational linguistics and data science. However, the United States, the United Kingdom, and Italy demonstrate higher average citations, suggesting greater influence per publication. This indicates that while Asian countries dominate in quantity, Western nations retain a leading edge regarding visibility, quality, and global recognition. Similarly, author-level analysis shows that productivity does not always translate into impact; researchers with fewer but highly cited works often exert greater intellectual influence than more prolific counterparts.

Thematic and keyword analysis reveal a consistent shift from lexicon- and rule-based sentiment analysis to data-driven and deep learning approaches. Keywords such as *deep learning*, *classification*, and *social media* illustrate the evolution of methods and data sources. Social media platforms, in particular, have become indispensable test beds for sentiment analysis due to their volume, variety, and immediacy of opinion-rich content. At the same time, the prominence of *semantics* and *computational linguistics* suggests that linguistic nuance and contextual understanding remain core challenges for sentiment analysis, even as technological sophistication advances. The results highlight that sentiment analysis has matured into a multidisciplinary research field, bridging linguistics, computer science, psychology, and business. The knowledge landscape demonstrates both opportunities—through integration of advanced AI methods and challenges, particularly in addressing bias, multilingualism, and explainability of sentiment models.

5. Conclusion

This study systematically mapped two decades of sentiment analysis research, tracing its evolution from opinion mining toward advanced deep learning and transformer-based approaches. The analysis of 2,394 publications indexed in Scopus (2004–2024) provides comprehensive insights into growth patterns, citation trends, productive authors, influential sources, leading countries, and thematic clusters. The results show that sentiment analysis is no longer confined to basic polarity detection but has expanded into nuanced applications across healthcare, finance, politics, and education. The steady increase in publications and the diversification of methods reflect its growing maturity and interdisciplinary scope. Despite firm productivity from Asian countries, Western nations dominate citation impact, indicating differences in visibility and global reach.

Thematically, the field is shifting toward deep learning, neural architectures, and large-scale language models while continuing to draw from semantic and linguistic traditions. However, persistent challenges remain, including dataset imbalance, contextual ambiguity, multilingual representation, and ethical considerations around bias and fairness. Sentiment analysis represents a vibrant and expanding field at the intersection of computational linguistics, AI, and social sciences. The present study contributes by mapping its intellectual structure and knowledge evolution, offering a reference point for scholars, practitioners, and policymakers. Future advances will likely emerge from integrating explainable AI, multimodal analysis, and cross-lingual approaches, ensuring sentiment analysis remains a cornerstone of modern data-driven decision-making.

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