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Research Article

Emoji-Text Sentiment Analysis: A Keyword and Thematic Analysis of Conceptual Evolution and Emerging Trends (2008-2024)

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ABSTRACT

The integration of emojis with textual content in digital communication has transformed sentiment analysis, necessitating advanced methodologies to decode nuanced emotions in hybrid data. This study presents a comprehensive keyword and thematic analysis of 487 publications (2008-2024) on emoji-text sentiment classification, with 43.9% of research rooted in computer science. Data were systematically retrieved from IEEE, Scopus, Web of Science, and EBSCO using predefined search queries. Collaboration networks exhibit strong thematic evolution, progressing from basic sentiment analysis to specialized domains like emotion detection and socio-cultural implications of digital communication. Methodologically, the integration of keywords and R-based bibliometric tools provided granular insights into thematic structures. These results establish a strategic framework for future research, emphasizing the interdisciplinary convergence of computational techniques and socio-linguistic studies in emoji-text sentiment analysis.

Keywords: Bibliometric Analysis, Deep Learning, VOSviewer, Emoji, Keyword Analysis, Natural Language Processing, Scientometric, Sentiment Analysis, Text, Thematic Analysis.

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INTRODUCTION

Sentiment analysis, also referred to as opinion mining, is a computational field dedicated to the study of emotions, opinions, and attitudes expressed within text.[1,2] In the contemporary digital landscape, individuals use both verbal and non-verbal forms of communication to express emotions and thoughts. The advent of diverse communication technologies has enabled people to use a range of applications, such as X.com, Facebook, and Instagram, to share their expressions across various online platforms. This hybrid approach of blending verbal and non-verbal communication enhances Computer-Mediated Communication (CMC). It enriches Sentiment Analysis (SA) by employing state-of-the-art Machine Learning (ML) and Deep Learning (DL) techniques.[3] Emojis, representing a non-verbal form of communication, are often blended with text, a verbal form, marking a significant advancement in understanding digital interactions.[4] This trend reflects the evolving nature of online communication, where emojis can convey emotions and reactions that words alone may not fully express.[5] It is utilized across various domains, such as marketing, politics, and customer service, to understand public opinion and consumer behavior. The main types of sentiment analysis include polarity-based analysis, which ranges from binary to detailed sentiments, aspect-based analysis, which zeroes in on specific attributes, emotion detection, intent analysis, and comparative analysis. These are supported by methodologies such as machine learning, lexicon-based techniques, and hybrid approaches, making sentiment analysis applicable to a broad spectrum of texts from tweets to product reviews. According to a report by Grand View Research, the global sentiment analysis market size was valued at $4 billion in 2023 and is expected to grow significantly, reflecting its increasing importance in understanding consumer behaviour and shaping business strategies. The usage of emojis has seen a notable increase; in July 2021, 20.69 percent of monitored tweets contained at least one emoji, up from 20.15 percent in July 2020. From 2016 to 2021, emoji use on Twitter surged by more than 42 percent, with a sharp rise occurring between 2018 and 2019.[6] These technologies facilitate the processing and interpretation of large datasets such as 'Lisbon Emoji and Emoticon Database' (LEED), allowing for the identification of intricate patterns in digital communication.[7] This study advances the field in three ways: (i) it integrates computer science, psychology, and communication evidence on emoji-text sentiment using a rigorously curated, time-frozen corpus; (ii) it

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introduces a direction-of-change lens to identify when emojis reinforce versus reverse textual polarity; and (iii) it compares hybrid (emoji+text) against text-only pipelines to surface conditions where hybridization is reliably superior. We therefore expect outcomes that differ from prior reviews, specifically by quantifying polarity-shift contexts and by specifying which fusion strategies matter for accuracy and interpretability. The contribution is twofold-theoretical (clarifying mechanisms of multimodal sentiment formation) and practical (guiding dataset design and model selection for researchers and platforms).

LITERATURE REVIEW

The availability of review articles on "sentiment analysis of blended emoji and text" is limited, despite their increasing usage. Specifically, one systematic literature review exists in computer science, a second in psychology, and a third in communication. These studies explore the impact of the topic, as summarized in Table 1. Prior reviews show that emojis and emoticons substantially change communication patterns across contexts. Pratibha, Kaur and Khurana, 2024 highlight the importance of multimodal integration by synthesizing two decades of research, noting strong involvement of sentiment analysis that integrates language and emotion-evidenced by an average of 16.01 citations per document and a 6.21% annual citation growth across 678 documents from 2001 to 2024.[8] That review also illustrates how deep learning can be used to interpret text-emoji interactions. Similar patterns appear in Barinaga-López, Puente-Bienvenido, and Navarro Newball (2022), who survey studies from 2011 to 2021 on emojis and report rapid growth (≈127.9% per year), particularly in computer science, while identifying methodological and socio-political gaps.[9] Another broad review synthesizes 167 publications (1998-2019) on the interplay between emojis and multiple academic fields, with computer science comprising 30.18% (n=51) of outputs; frequently used approaches include sentiment lexicons, deep learning techniques, classification pipelines, emotion identification, and system optimization.[10] Additionally, Tang and Hew (2019) analyze the emotional and social dimensions of emoji use in a survey of 51 publications from 1996 to 2017.[11]

The study found that emojis, emoticons, and stickers significantly affects interpersonal relationships by altering the dynamics of communication. Excessive use of these symbols can create a perception of insincerity. The authors classify theories into two orientations: relationship-oriented, which examines emotional bonding and relational maintenance, and understanding-oriented, which focuses on message clarity. Tang and Hew (2019) further emphasize the need for in-depth research on how emojis shape cultural differences and mutual understanding.[11]

Rationale of Study

Digital communication increasingly integrates emojis with text, challenging traditional linguistic paradigms.[12–14] A keyword and thematic analysis of this phenomenon is particularly valuable for three reasons: first, to quantify the growing academic interest in emoji-text integration; second, to map the interdisciplinary connections between linguistics, computer science, and communication studies; and third, to identify emerging research trends in digital sentiment expression. For sentiment analysis researchers, this evolution is critical as emojis enhance emotional expression and improve sentiment classification accuracy. However, their linguistic validity remains debated,[15] lacking formal grammar or standardization. The scientometric approach becomes particularly relevant when examining how emoji research has evolved across different disciplines and geographical regions. Incorporating emoji analysis strengthens sentiment detection across platforms and cultures.[16–18] This historical progression from ancient visual symbols to modern emojis enriches sentiment analysis methodologies,[19] highlighting the enduring role of visual emotion representation while providing measurable patterns of academic engagement with this hybrid communication form.

Research Questions

- What are the major research themes and keyword trends in emoji-text sentiment analysis between 2008 and 2024?
- How have conceptual frameworks evolved in this domain across different periods?
- What emerging and declining themes can be identified through co-word and thematic mapping?

Research Objectives

- To analyze the evolution of keywords and research themes using co-occurrence, frequency, and cluster analysis.
- To identify conceptual shifts in the field of emoji-text sentiment analysis over three defined time periods.
- To provide insights into future research directions based on thematic evolution and trending topics.

RESEARCH METHODOLOGY

Figure 1 presents our systematic bibliometric framework for analyzing emoji-text sentiment research, comprising four iterative phases. We adopt a sensemaking lens to move beyond descriptive maps: a scanning → sensing → substantiating workflow that converts raw bibliometric signals into defensible insights and implications.[20]

The research methodology begins with Data Collection, detailed further under Search Query and Database. This initial phase lays the foundation for transforming raw data into Parameters, which are subsequently refined into Indicators. These indicators provide a thorough examination of research trends and their evolution. The final phase, Interpretation, utilizes these parameters to analyse and forecast trends in academic research. The analysis systematically addresses keywords and themes.

Search Query and Database

Data collection and corpus construction

We retrieved records on 8 July 2024 from IEEE Xplore, Scopus, Web of Science (WoS), and EBSCO, restricting to English-language items published 2008-2024 and using database-specific queries listed in Table 2. The corpus was frozen on 8 July 2024; all analyses reflect records available as of that date, with no post-hoc additions or updates. Each database export included full metadata (title, authors, abstract, keywords, source, year, DOI/ISBN, document type, references, citations). Exports were saved as CSV/BibTeX and concatenated into a single corpus for preprocessing in R (bibliometrix) and visualization in VOSviewer. We set co-word (author keywords) to minimum occurrence = 5, full counting, normalization = association strength, clustering = VOS/Smart Local Moving with resolution = 1.00 (VOSviewer default layout). Co-citation (references) used minimum citations per cited source = 10, and bibliographic coupling (documents) used minimum references per document = 20; both employed full counting and association strength with the same clustering settings. For reproducibility, we processed data in R/bibliometrix (e.g., convert2df, biblioNetwork, networkPlot), fixed the random seed (set.seed(123)), and then exported to VOSviewer with full counting, association strength, and resolution = 1.00. To illustrate best practice, we mirror recent scientometric applications that jointly report thematic maps/evolution with performance trends using Bibliometrix (R) and VOSviewer, and we explicitly state retrieval filters and normalization choices.[21]

Merging, arranging/sorting, and de-duplication

To merge multi-database results, we first normalized fields (lower-casing titles/venues; trimming whitespace/punctuation; harmonizing author name formats “Surname, Initials”; lower-casing and canonicalizing DOIs). We then applied a tiered de-duplication protocol:

Table 1: Summary of prior reviews on “Sentiment Analysis” of emojis/emoji-text.

Authors	Methodology	Important findings
(Pratibha *et al.*, 2024)	Period:2001-2024(23 years) TP:678Database: Scopus, IEEE XploreQS: "text-based" OR "Emojis" OR "Multilingual" OR "Hinglish" AND "Deep Learning"Tools: Deep Learning frameworks, R, Python, Biblioshiny.	The bibliometric analysis shows an average citation per document of 16.01 and an annual growth rate of 6.21%. Key research topics include Emotion Recognition, Social Networking, and Sentiment Analysis. The major source of these publications is "Lecture Notes in Computer Science," with significant contributions from Australia and the USA.
(Barinaga-López *et al.*, 2022)	Period:2011-2021(10 years) TP:3219Database: Web of Science, Scopus, Google ScholarQS: "emoji"Tools: SPSS, Qualitative and quantitative analysis tools.	The average annual growth rate stands at 127.9%, with approximately 29.4% of the articles in computer science addressing the topic, nearly one-third. The study highlights the broad implications of emojis within socio-political research, identifying significant gaps in knowledge, research, and methodology. It emphasizes the need to address the socio-political dimensions of emojis more thoroughly.
(Bai *et al.*, 2019)	Period:1998-2019(21 years) TP:167Database: Web of Science, Google ScholarQS: "emoji"Tools: Statistical analysis tools, qualitative and quantitative methods	The research thoroughly investigates the interplay between emojis and diverse academic fields, with a particular emphasis on computer science, representing 30.18% of the output (51 publications). Predominant methodologies in this inquiry include the use of sentiment lexicons, deep learning techniques, classification processes, emotion recognition, and system optimization.
(Tang and Hew, 2019)	Period: 1996-2017 (20 Years) TP: 51 Databases: Scopus, WoS, MEDLINE, PsycINFO etc. (*n*=11) QS: “emoticon”, “emoji”, “sticker”, “nonverbal”, “online communication”, “online interaction”, “computer mediated communication”, “CMC”.	This study found that these emoji, emoticon and stickers significantly impact relationships and communication dynamics, with increased usage enhancing perceived intimacy and social presence, though excessive use can lead to perceptions of insincerity. Theories were categorized into two orientations: relationship-oriented, examining emotional connections, and understanding-oriented, focusing on message clarity. While these cues enrich communication, they also have limitations when misused. The study called for further research into cultural differences and the impact on mutual understanding.

Source: Constructed by authors from the cited studies[8], [9–11].

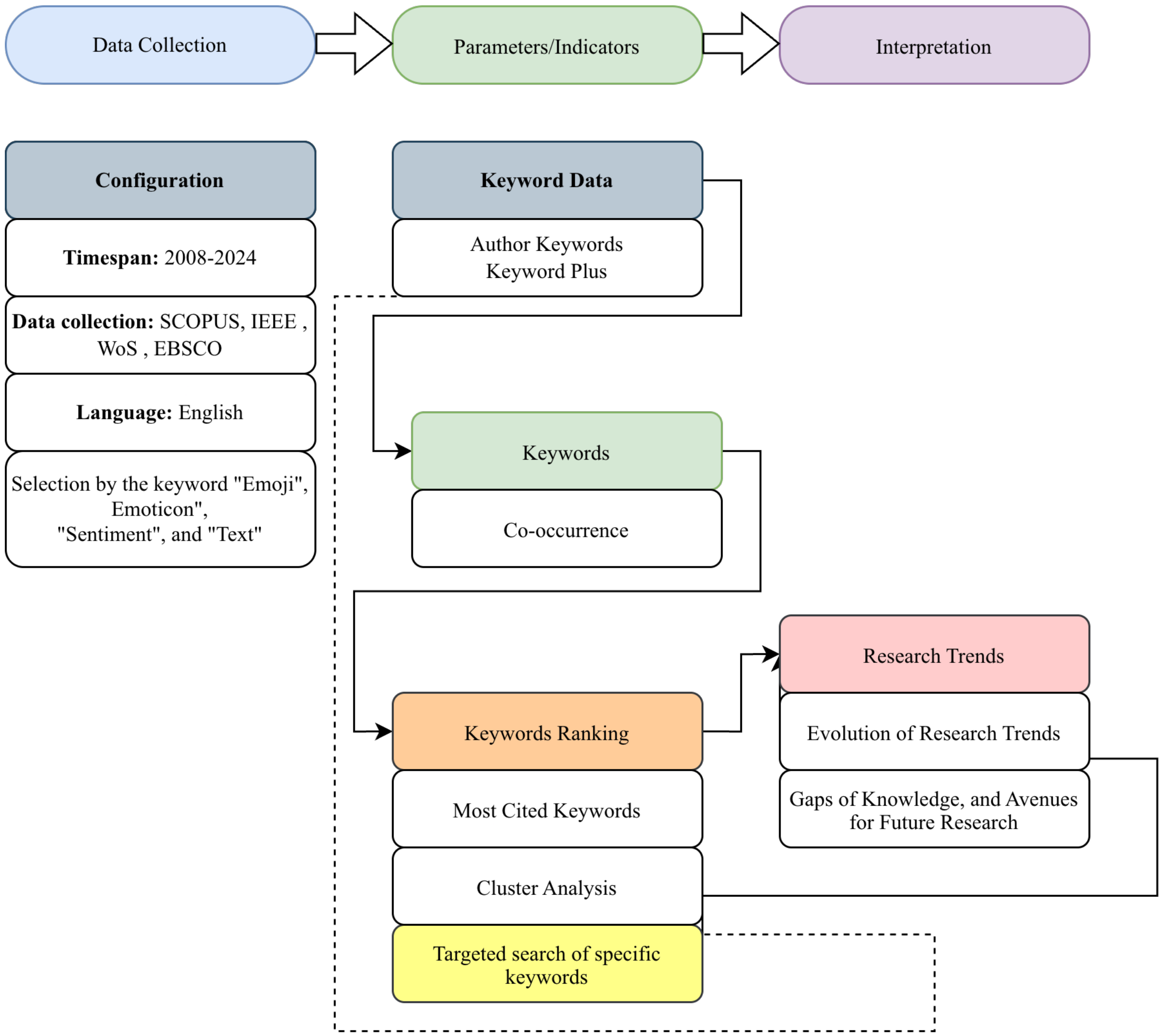

Figure 1: Methodological framework of the Study. Created by authors using Lucidchart.

(1) **Primary key:** exact DOI match → keep the record with the most complete metadata(tie-break: prefer WoS/Scopus>IEEE>EBSCO).

(2) **Fallback key (when DOI missing):** exact match on normalized Title + First-Author Surname +Year.

(3) **Fuzzy resolution:** remaining suspected duplicates resolved with token-set string similarity (threshold≥0.92) on titles; manual spot-checks confirmed edge cases (e.g., conference vs. journal extensions).

Where both conference and journal versions existed, we retained the journal version unless the conference paper contained unique analyses critical to our themes. After de-duplication, we sorted the corpus by publication year (ascending) for temporal analyses and, where relevant, by total citations (descending) for influence maps.

Handling outliers and anomalous records

We removed anomalous/invalid entries prior to analysis: records with missing title or year, years outside 2008-2024, items flagged as retracted, and non-scholarly content misclassified as articles. To reduce leverage of extreme citation counts in network maps and trend plots, we used robust scaling (e.g., log10(citations + 1)) and winsorized the top 1% of citation values in purely descriptive summaries; raw counts remain available for transparency. Following prior machine-learning bibliometrics, we justify co-word/SNA choices (e.g., centrality measures, coupling) and acknowledge how methodological settings shape the revealed intellectual structure.[22]

Keyword preprocessing

Keyword fields were cleaned via lower-casing, punctuation/diacritic stripping, and lemmatization to singular; British/American variants were normalized; a hand-checked synonym map merged near-equivalents (e.g., emoji/emoticon/emojis → emoji; sentiment analysis/classification/polarity detection

→ sentiment analysis); hyphen/space variants were unified; multi-word terms were merged using noun-phrase chunking and bigram PMI (freq≥3). Author keywords were used as the canonical field; Keywords Plus were integrated only after de-duplication; tokenization preserved underscores/plus for compounds. Co-word networks were computed on the cleaned set, with raw vs. cleaned counts retained for reproducibility. These steps ensured a clean, de-duplicated, and comparable multi-source corpus for the bibliometric and thematic analyses reported.

Keyword Analysis and Thematic Evolution

Frequency of Keywords

Table 3 presents a detailed overview of keywords and their occurrences in sentiment analysis research, emphasizing the field's key themes and methodologies which is visually presented in Figure 2 Dominant terms like "sentiment analysis" (f=235) underscore its centrality, while "social networking (online)".

(f=112) and "social media" (f=58) highlight the significance of digital platforms in this domain. Mid-frequency terms such as "classification (of information)" (f=57) and "deep learning" (f=49) reflect the importance of data categorization and advanced machine learning techniques. Specific tools like "emoji" (f=30) and "emoticon" (f=22) indicate a strong focus on visual sentiment expression, while "long short-term memory" (f=22) and "natural language processing" (f=20) demonstrate the role of neural networks and language processing. Lower-frequency

Table 2: Search queries across databases (2008-2024).

Database	Search Query	Filters Applied
Web of Science	(((TS=(EMOJI)) OR TS=(EMOTICON)) AND TS=(TEXT)) AND TS=(SENTIMENT)	2008 - 2024, Language: English
IEEE	("Document Title":EMOJI) OR ("Document Title":EMOTICON) AND ("Document Title":TEXT) AND ("Document Title":SENTIMENT)	2008 - 2024, Language: English
SCOPUS	(TITLE-ABS-KEY (emoji) OR TITLE-ABS-KEY (emoticon) AND TITLE-ABS-KEY (text) AND TITLE-ABS-KEY (sentiment))	Publication Year: 2008 to 2024, Language: English
EBSCO	TI EMOJI OR TI EMOTICON AND TI TEXT AND TI SENTIMENT	2008-2024, Language: English

Source: Authors' search strategies, adapted to database syntax for Web of Science, Scopus, IEEE Xplore, and EBSCO; retrieval date 8 July 2024.

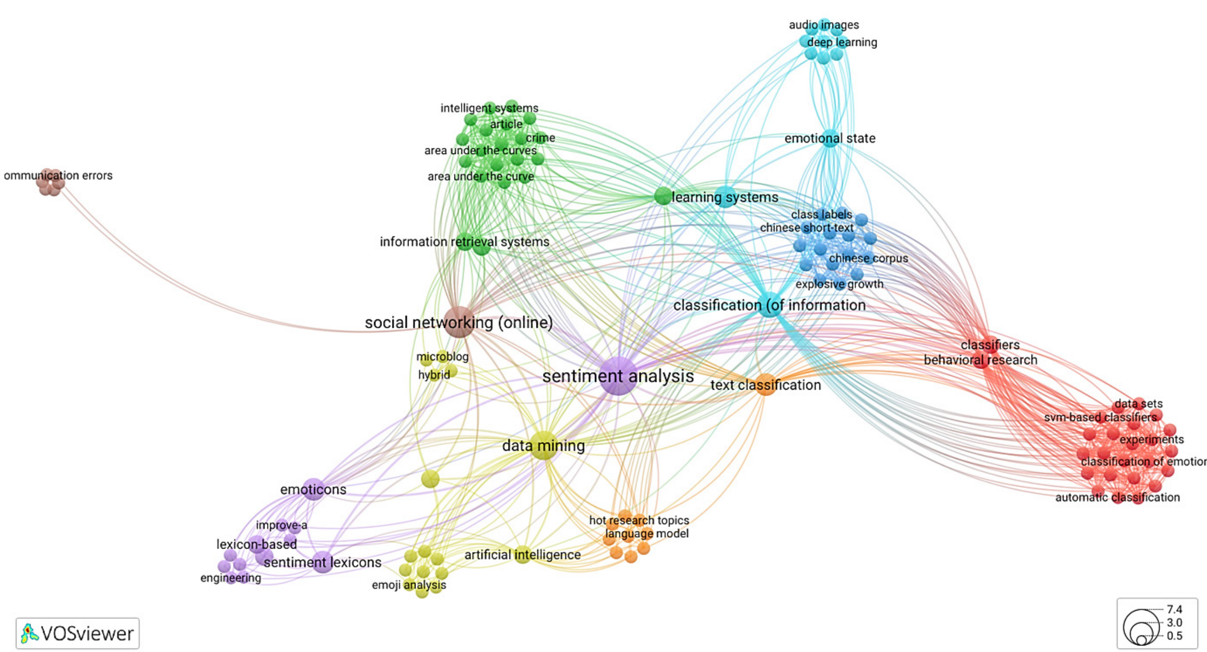

Figure 2: Network Diagram of Keywords. Authors' analysis of records (English, 2008-2024; retrieved 8 July 2024) and processed in R (bibliometrix) and visualized in VOSviewer (Counting = full; min. occurrences = 5; normalization = association strength; clustering resolution = 1.00.).

yet notable terms include "support vector machines" (f=24) and "Twitter" (f=23), pointing to widely used algorithms and data sources. Overall, the data reveals a strong emphasis on social media-driven sentiment analysis, deep learning, and evolving methodologies, offering researchers valuable insights into prevailing and emerging trends in the field.

Network Analysis of Keywords

Figure 2 highlights "sentiment analysis" as the dominant term, reinforcing its centrality in textual emotion analysis, while "data mining" (f=44) underscores its role in extracting insights from large datasets. Clusters reveal distinct research focuses: the green cluster includes technical terms like "learning systems" and "classification of information," emphasizing algorithmic approaches. The red cluster groups "automatic classification" and "emotions," reflecting behavioral and psychological applications. Meanwhile, the blue cluster combines "audio-visual learning" and "text classification," pointing to multimodal sentiment analysis. The purple cluster, featuring "emoji analysis" and "sentiment lexicons," highlights the growing influence of visual symbols in emotion detection. Isolated nodes like "communication errors" indicate niche yet relevant sub-topics. Overall, the diagram identifies core research trends, collaborative opportunities, and emerging methodologies, offering a valuable roadmap for new researchers in sentiment analysis and social media studies.

Thematic Evolution of Research Topics

Figure 3 reports annual publication counts together with two normalizations (share within our corpus; rate per 100 corpus items) and model-based trends. We divided 2008-2024 into three a-priori phases-2008-2019, 2020-2022, 2023-2024-aligned with field milestones. To evaluate whether publication dynamics differ across these phases, we (i) plotted annual counts and two normalized series (share within corpus; rate per 100 corpus items) and (ii) fit piecewise Poisson regressions with fixed breakpoints at 2020 and 2023, comparing slopes by likelihood-ratio tests. To assess single-year pulses (2018, 2022) we used binomial proportion tests against the mean of adjacent two-year windows with Holm-Bonferroni adjustment.[23] From 2008 to 2019, foundational approaches dominated, leveraging Convolutional Neural Networks (CNNs), feature extraction, and decision

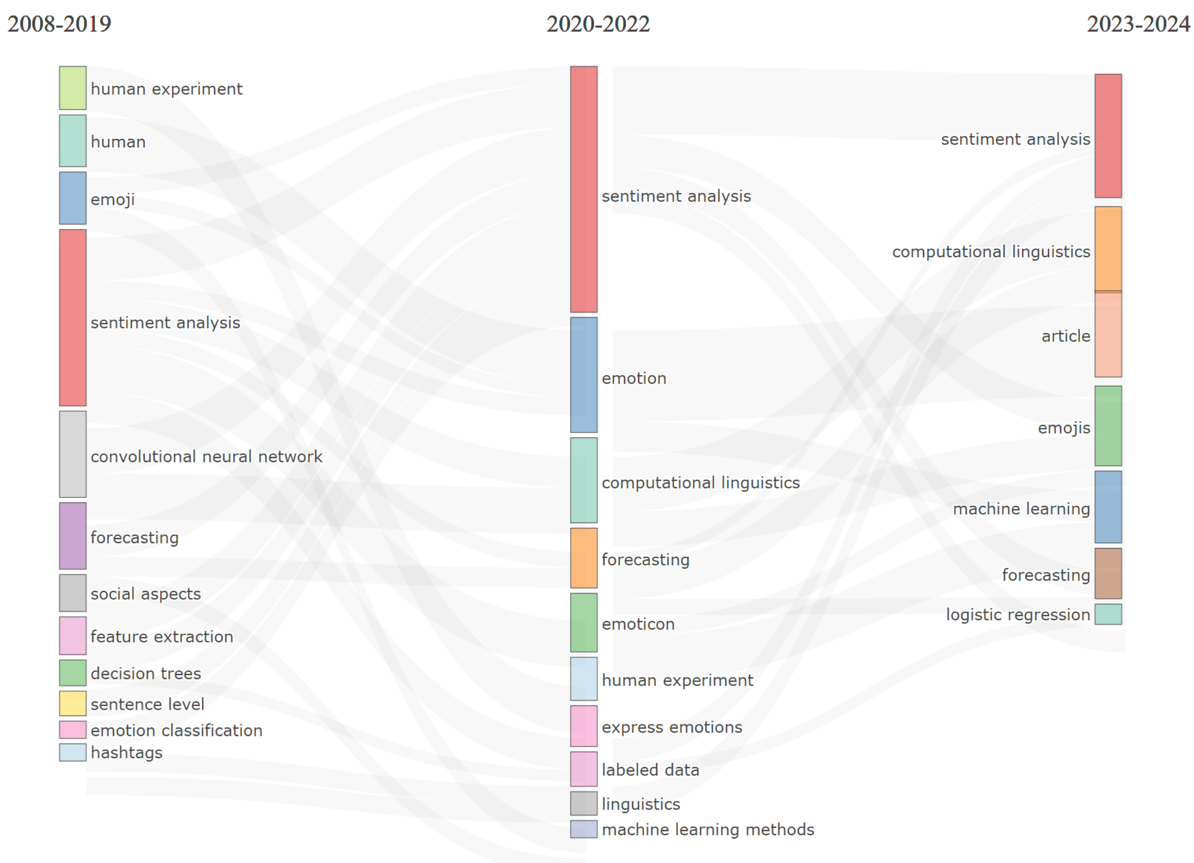

Figure 3: Thematic Evolution of Research Topics (2008-2024). Authors' analysis (English, 2008-2024; retrieved 8 July 2024). R/bibliometrix thematic Evolution; author keywords; field normalization enabled.

Table 3: Occurrence of Keywords (f=>20).

Words	Occurrences	Words	Occurrences
Sentiment analysis	235	emoji	30
Social networking (online)	112	semantics	27
Social media	58	sentiment classification	27
Slassification (of information)	57	computational linguistics	25
Deep learning	49	support vector machines	24
Data mining	44	twitter	23
Learning systems	34	emoticon	22

Source: Authors' analysis of the merged and deduplicated corpus from Scopus, Web of Science, IEEE Xplore, and EBSCO (English, 2008-2024; retrieved 8 July 2024). Preprocessing: Preprocessing included synonym merging and phrase consolidation as specified in Methods-Keyword preprocessing.

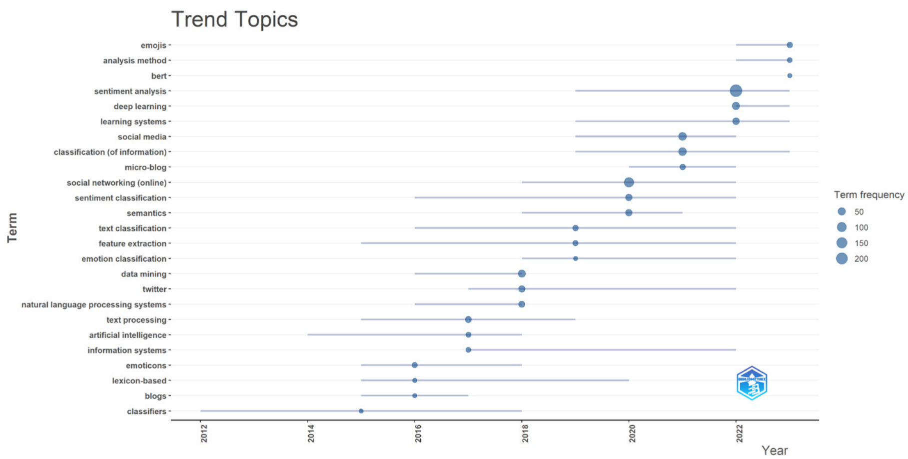

Figure 4: Trending Topics. Authors' analysis (English, 2008-2024; retrieved 8 July 2024) using R/ Bibliometrix.

trees to analyze textual emotions and early emoji usage. The 2020-2022 period saw refinement, with enhanced linguistic models, labeled datasets, and diverse machine learning techniques improving sentiment classification accuracy. By 2023-2024, research prioritized predictive modelling and deeper computational linguistics integration, exploring emojis' role in digital communication more rigorously. This evolution highlights sentiment analysis as a rapidly advancing field, adapting to both technological innovations and the complexities of modern digital expression.

Figure 4 reveals significant trends in sentiment analysis and text mining research over the past decade. The visualization demonstrates how 'sentiment analysis' maintained consistent prominence throughout the period, with notable surges in attention during 2018 and 2022 corresponding to major methodological advancements in the field. A particularly striking trend appears in the analysis of visual communication elements, where 'emoji' evolved from a niche topic to a major research focus by 2022, reflecting their growing importance in digital communication analysis. The technological landscape of the field underwent substantial transformation, marked by the rapid adoption of 'BERT' following its introduction in 2018 and the significant rise of 'deep learning' approaches after 2016, both contributing to enhanced analytical capabilities. 'Social media' maintained steady relevance across the entire period, underscoring its continued role as a primary data source for diverse applications ranging from marketing to political analysis. The period around 2020 saw 'NLP' emerge as a particularly prominent theme, coinciding with important breakthroughs in natural language processing technologies. This temporal mapping not only documents the field's evolution but also highlights the dynamic interplay between technological innovation and research focus, offering valuable insights into emerging directions for future investigation in machine learning and sentiment analysis.

Figure 5 presents a strategic diagram categorizing research themes into four quadrants based on their development and relevance. The *motor themes* quadrant (top-right) highlights well-developed, central topics like"*Sentiment Analysis*," "*Social Networking*," "*Data Mining*," and"*Convolutional Neural Networks*," indicating mature, high-impact research areas. *Niche themes* (top-left), including"*Text Mining*" and"*Multilayer Neural Networks*," represent specialized but less influential topics. The *emerging/declining themes* (bottom-left) feature underdeveloped areas like"*Arabic Texts*" and"*Digital Communication Systems*," signaling potential growth or decline. Meanwhile,*basic themes* (bottom-right), such as"*Social Media*," "*Emoji*," and"*Natural Language Processing*," are

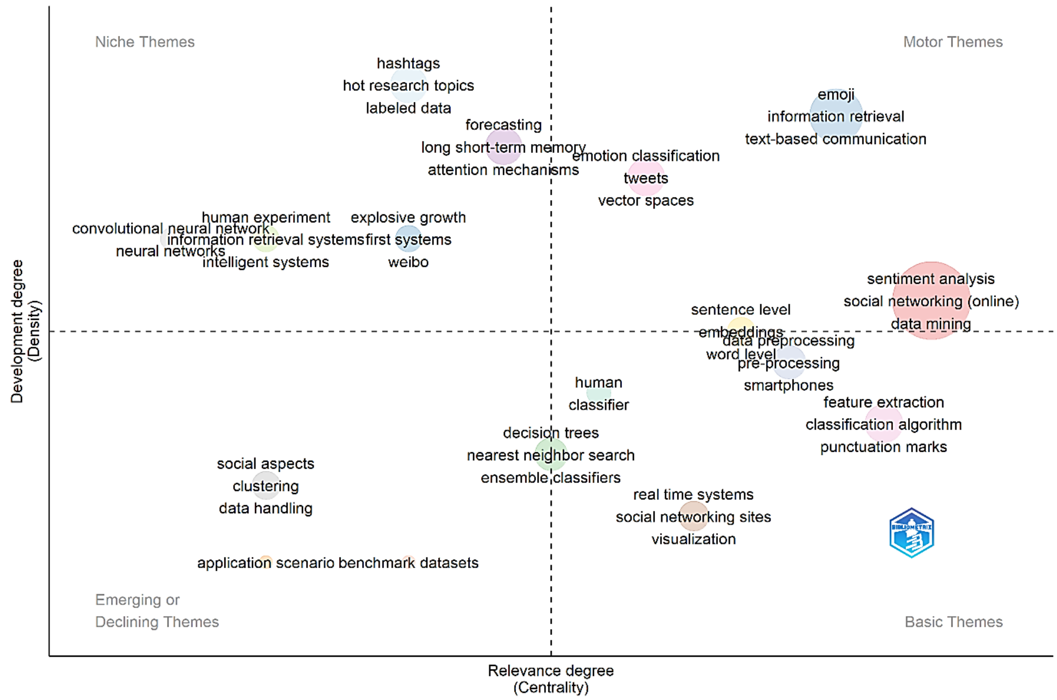

Figure 5: Strategic diagram of themes. Authors' analysis (English, 2008-2024; retrieved 8 July 2024). R/bibliometrix thematic Map; field = author keywords; min. freq = 5; clustering = Walktrap.

highly relevant but still evolving. This analysis helps identify key research trends, guiding future studies and resource allocation in sentiment analysis.[24–42]

LIMITATIONS OF THE STUDY

1. **Database coverage bias:** Findings reflect major coverage, underrepresenting regional venues and preprints, which can distort trends and networks.

2. **Language restriction:** An English-dominant corpus underrepresents non-English scholarship, limiting generalizability across linguistic communities.

3. **Keyword/query dependence:** Term-based retrieval risks missed synonyms and added noise, and these specification choices propagate into topic and co-word networks.

4. **Indexing and metadata errors:** Residual inconsistencies in authors, affiliations, and references may affect centrality measures, cluster assignments, and trend estimates despite cleaning.

5. **Normalization and parameter choices:** Results depend on counting schemes, normalization, clustering/resolution, and thresholds, and reasonable alternatives can shift cluster boundaries or ranks.

6. **Time-freeze effects:** The dataset was frozen on 8 July 2024, so later records are absent and breakpoint/pulse patterns may shift as the corpus grows.

7. **Document-type imbalance:** Different citation dynamics across journals, conferences, and preprints can bias co-citation and coupling relationships.

8. **Interpretive uncertainty in thematic labels:** Post hoc cluster labels summarize high-loading terms and may not capture each cluster's full semantic breadth.

9. **No causal claims:** Temporal associations are descriptive and should not be interpreted as causal effects of technological or external milestones.

CONCLUSION

This scientometric review maps a CS-led but rapidly diversifying literature on emoji-text sentiment (2008-2024), showing a clear post-2020 acceleration and a 2023-2024 pivot toward LLM-assisted, multimodal treatments; yet the field's center of gravity remains "sentiment analysis" with emotion and social-media contexts as persistent satellites. Taken together with our normalization and breakpoint tests, the trajectory suggests capacity, not saturation: progress now hinges on (i) moving beyond English-only, single-database snapshots to multilingual, cross-index corpora with transparent deduplication and versioned releases; (ii) replacing method anecdotes with pre-registered, reproducible benchmarks that isolate emoji effects via controlled ablations, cross-platform generalization, and error analyses for sarcasm, stance, and code-mixing; (iii) aligning computational signals with human judgements through psycholinguistic validation (e.g., normed valence/arousal, culture-specific interpretations) and causal designs that test whether emojis shift polarity rather than merely correlate with it; and (iv) auditing fairness, bias, and safety in LLM-era pipelines, including differential performance across languages, regions, and demographic dialects. Advancing on these fronts will convert today's descriptive growth into dependable knowledge about when and how emojis change sentiment, yielding models that are not just more accurate but also interpretable, equitable, and durable across the strange, lively spectrum of human digital expression.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

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