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Sentimental analysis of social networks: A comprehensive review (2018-2023)

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Abstract The field of sentiment analysis, a burgeoning field dedicated to deciphering emotions, opinions, and attitudes within text data, has experienced remarkable growth in research interest. This review paper embarks on a comprehensive journey through the dynamic landscape of sentiment analysis, encapsulating its multifaceted dimensions across three prominent academic databases—Scopus, the IEEE Xplore Digital Library, and the Wiley Online Library—spanning from 2018 to 2023. This paper establish the significance of sentiment analysis, charting its evolution from 2008 and elucidating its multifarious applications across domains. We underscore the necessity of drawing insights from diverse databases, transcending the confines of a single source. "On the causality of temporal sentiment analysis," delves into the intricate interplay between sentiment signals and other variables, echoing Granger causality theory from econometrics. We unveil the burgeoning adoption of Granger causality in examining stock market dynamics and sentiment analysis, shedding light on the predictive causality landscape. The temporal dimension takes centre stage "On the temporal dynamics of sentiment analysis," where we explore how sentiment fluctuates over time, particularly during transformative events such as the COVID-19 pandemic. We scrutinize the evolution of emotional appeals in political campaigns and the pivotal role of sentiment analysis in detecting online bullying and suicidal ideation. "On the reproducibility and practical application," we deliberate on the challenges and prospects of implementing sentiment analysis techniques in real-world scenarios. We navigate the intricate landscape of reproducibility and translate research insights into actionable strategies."Discussion and conclusion," encapsulates the essence of our journey. We highlight content variations across databases and unravel the evolution of techniques. We contemplate the bridge between academia and industry by presenting an integrated view of sentiment analysis. As the sentiment analysis field evolves, this review paper offers a panoramic view of its past, present, and future. It is a valuable resource for researchers and practitioners seeking to navigate the ever-expanding horizons of sentiment analysis across diverse databases and domains.

Keywords: sentiment analysis, social networks, temporal dynamics, causality, sentiment techniques

1. Introduction

Sentiment analysis, a field of study that analyses the emotions, opinions, and attitudes expressed in text data, has garnered significant research interest since 2008, as evidenced by a growing number of published papers. This trend is discernible across reputable research databases, including Scopus, the IEEE Xplore Digital Library, and the Wiley Online Library, demonstrating its multifaceted applications and increasing relevance (Belaz et al., 2016; Rajalakshmi et al.,2017; Hemmatian et al., 2019). From 2008 to 2022, the number of publications related to "sentiment analysis in social networks" exhibited an impressive annual growth rate of 43%.

Prior reviews of sentiment analysis, particularly in the context of social networks, have focused primarily on two key aspects. First, various techniques, such as machine learning algorithms, lexicon-based approaches, and hybrid methodologies, have been examined (Ravi et al., 2015; Zhang et al., 2020). Second, these reviews delved into specific application domains encompassing emergencies, business intelligence, marketing, and prediction of election results, among others. Fig. 1 provides an illustrative representation of this classification (Granger et al., 1969; Jiang et al., 2019).

Unlike the previous authors, we are not confined to a single database. Instead, we draw upon a wider range of resources, including Scopus, IEEE, and Wiley, to provide a more comprehensive overview of sentiment analysis in social networks. This allows us to present a more expansive and inclusive perspective (Bouktif et al., 2020; Birjali et al., 2021).

(1) The abstract highlights the importance of sentiment analysis in social media and the need for a systematic arrangement of prior efforts in this area (Yu et al., 2021; Park et al., 2021). It aims to analyse the progress, present advances, and outline limitations in sentiment analysis. This paper categorises and compares various techniques and methods used in sentiment analysis and introduces different types of data and advanced tools for research.

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(2) This paper provides an overview of sentiment analysis and emotion detection from text, highlighting the importance of understanding human psychology by analysing textual content on social media platforms. The paper discusses the levels of sentiment analysis, various emotion models, and the sentiment analysis and emotion detection process. The paper also addresses the challenges faced during sentiment and emotion analysis.

(3) This paper proposes an unsupervised approach for sentiment and emotion analysis of unstructured social media text, achieving an accuracy of 80.68%. The proposed approach outperforms the lexicon-based approach, which achieves an accuracy of 75.20%.

(4) The sentiment analysis in this paper focuses on the document level, where sentiments are summarised as positive or negative for the entire document. This approach is faster but not suitable for precise evaluation and comparison (Chatterjee et al., 2020; Hu et al., 2020). Most techniques used in document-level opinion mining are based on supervised learning methods.

Numerous research studies have examined how written messages, particularly those on social media, express sentiment, as was already established (Ashima et al., 2020; Xiang et al., 2014). These studies offer a thorough overview of the attitudes and viewpoints of users. However, this method prevents us from analysing causal linkages or how sentiment evolves. Furthermore, one might need to fully reflect the particular context and circumstances of the particular domains where the analyses are being used (Xianghua et al., 2013). Because it is frequently challenging to replicate the methodologies, many of these studies need to provide a complete, comparative study of the various techniques utilised by different authors (Nielsen et al., 2019). A few papers also discuss the industry's use of sentiment analysis, raising the possibility of a gap between academic research and business operations (Singh et al., 2014).

In contrast, our research paper takes a distinct approach. We steer clear of delving into specific application domains and, instead, delve into a comprehensive analysis of the various techniques used for sentiment analysis (Hoque et al., 2019). Our exploration encompasses lexicon-based approaches, machine learning algorithms, and hybrid tools to provide a holistic understanding of the field.

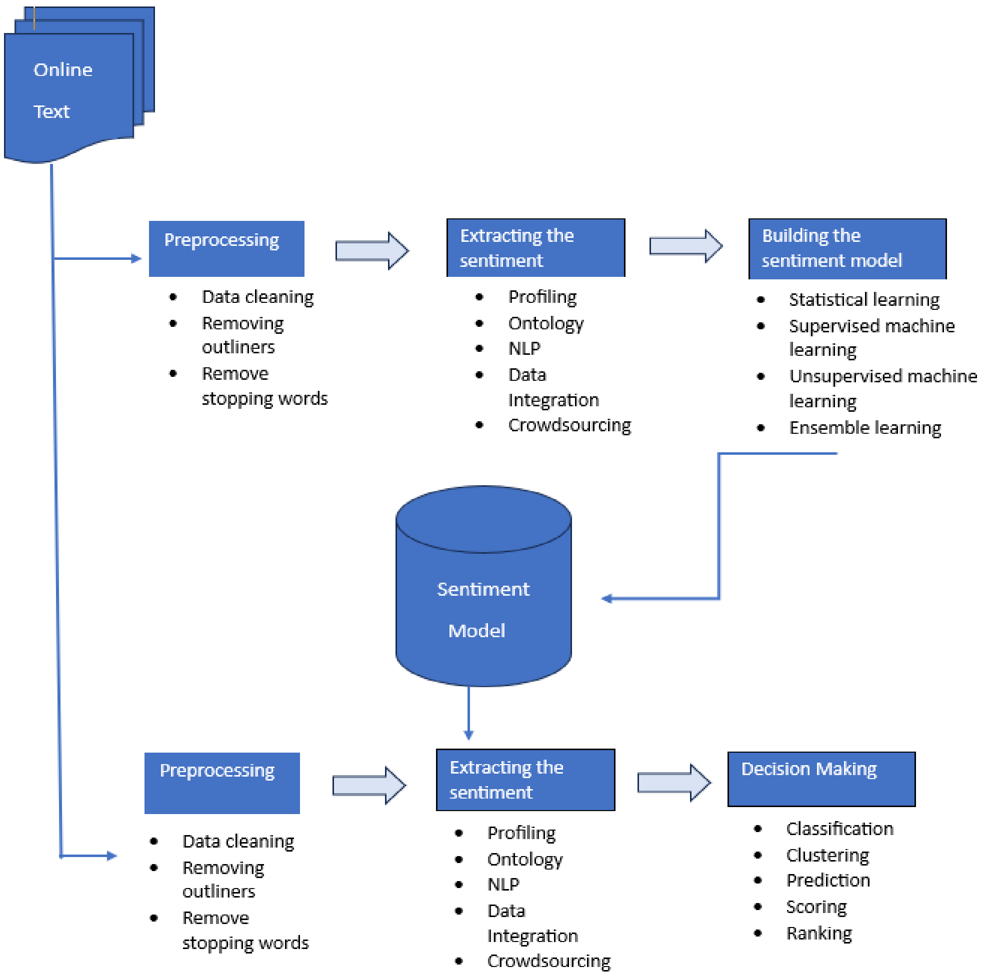

Figure 1 Representation of the classification system.

Previous studies by authors such as Ravi (2015), Balazs and Velazquez (2016), Rajalakshimi et al. (2017), Chaturvedi et al. (2018), and Hemmatian and Sohrabi (2019) have focused primarily on specific facets of sentiment analysis. These include summarising papers published between 2018 and 2023, exploring opinion mining, and reviewing classification techniques. In contrast, our work strives to bridge the gap between academic research and commercial practices, offering a more integrated view of sentiment analysis techniques and their real-world applicability (Moraes et al., 2023; Socher et al., 2013).

In the subsequent sections, we delve into the academic and commercial aspects of sentiment analysis (Raaijmakers et al., 2008). We explore temporal analysis, causal relationships, and the tools available for commercial sentiment analysis (Kaur et al., 2014). Additionally, we will provide insights into the various techniques used for sentiment analysis and their publications in Scopus, IEEE, and Wiley. Finally, we will consider practical considerations for implementing state-of-the-art methods and briefly discuss the findings (Wan et al., 2019).

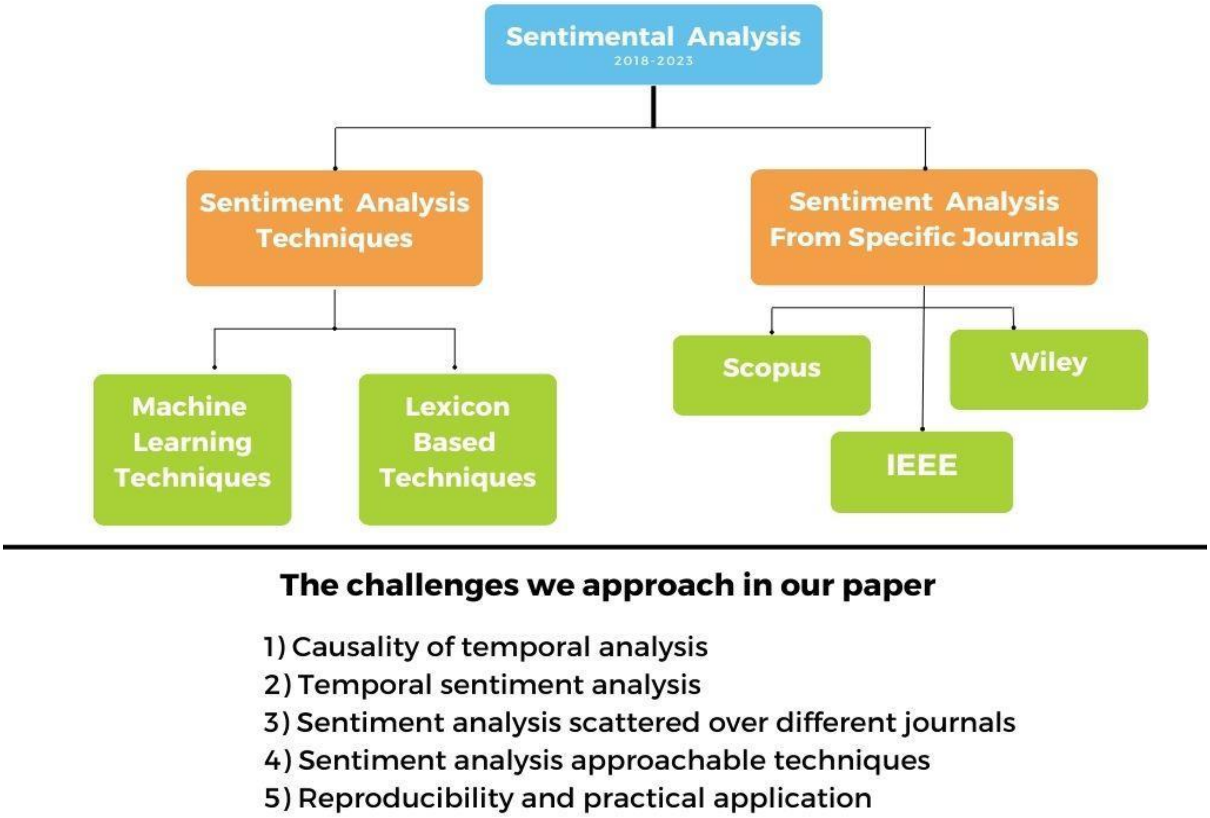

Figure 2 Classification of sentimental analysis techniques and specific journals used, i.e., Scopus, Wilcoxon and IEEE (2018-2023).

2. Unravelling the Causal Connection of Temporal Sentiment Analysis

Understanding how much sentiment signals affect other important variables is a common research focus in sentiment analysis. Consider the inquiry into whether the stock market value (y(t)) of a particular firm could be impacted by the sentiment signal (s(t)) derived from brief messages relating to the company (Bagheri et al., 2013; Thelwall et al., 2012). It is important to note that additional exogenous factors could be involved. However, for the sake of simplicity, we refer to one of these variables as x(t) and temporarily ignore the difficulties of data sampling (Wollmer et al., 2010; Gunes et al.,2010).

The association between time-sampled sentiment signals and the variable of interest is frequently found inadequate from a statistical and practical standpoint (Agrawal et al.,2023; Pang et al., 2021). In recent years, scholars have been motivated by the notion of Granger causality in econometrics, developed by Granger (1969), to explore this relationship more deeply. According to the theory of Granger causality, a time series can be considered a Granger causal for another time series if it offers statistically significant forecasting data for the latter's future values . A statistical hypothesis is used to test this idea, with the null hypothesis claiming that, under the assumption that both time series are stationary, s(t) does not Granger-cause y(t). The variable of interest is written in equation (1), and a univariate autoregression model is fitted to it using the statistical method described by Chvostekova (2019):

$$y(t) = a_0 + \sum^{M}_{m=1} a_m y(t - m\tau) + e_0(t) \qquad (1)$$

The sentiment signal s(t) is then included in the model by adding lagged samples, as shown in equation (2):

$$y(t) = a_o + \sum^{M}_{m=1} a_m y(t - mt_o) + \sum^{N}_{n=1} b_n s(t - nt_1) + e_1(t) \qquad (2)$$

In these equations, τ represents the basic lag for each signal, and $e_0(t)$ and $e_1(t)$ signify the noise residuals of the regression. The incorporation of exogenous variables into this data model can be seamlessly achieved using a vector autoregressive approach. Acceptance of the null hypothesis (s(t) does not Granger-cause y(t)) is contingent upon the exclusion of lagged values of s(t) in the regression model.

It is crucial to clarify that Granger causality, as used in econometrics, applies only to predictive causality and not to the causality seen in physics (Read et al., 2005; Sindhwani et al., 2008). The past ten years have seen a significant increase in the popularity of Granger causality, which is now essential for understanding time series processes in various disciplines, such as economics, genetics, climate studies, and neurology (Thelwall et al., 2019; Thomas et al., 2016).

Numerous studies have used Granger causality tests to anticipate stock market patterns using social media data, a highly dynamic area of study, and have also used predictive causality in sentiment analysis. Early contributions can be linked to studies examining the relationships and forecasting power between investor sentiment and the Shanghai Composite Index (Yong yong et al., 2020; Jian et al.,2023).

Granger causality tests have changed over time, spanning numerous study focuses and horizons. For instance, a study by Zhang et al. (2020) explored the connection between stock prices and investor sentiment in the Growth Enterprise Market Finger Bar of Eastmoney, considering scenarios where rational arbitrageurs and noise traders affect markets, particularly in semiefficient markets such as China. By studying 6,000 postings and using Bayesian data models to link stock prices to their investor bullish index, they discovered several unexpected dynamics: forums had a long-term impact on prices, while prices had a short-term impact on forums. However, caution should be used when making predictions based on sentiment cues.

Min Yang et al. proposed a multisource domain adaptation method called MDA-GC for cross-domain sentiment classification, outperforming other methods (Kyung et al., 2010; Weishu et al., 2010).

MDA-GC utilises a sentiment-guided capsule network to capture domain invariant knowledge and an attention mechanism to assign importance weights to different source domains. It also introduces a Granger causal objective to ensure that the weights assigned to individual experts correlate strongly with their contributions to the decision.

Much research on emotion and stock market causality has encouraged methodological variation and sparked theoretical discussions. A thorough investigation by Bouktif et al. (2020) sought to reconcile two opposing theories: (a) the random walk hypothesis, which contends that prices are determined arbitrarily and make stock prediction impossible, and (b) the hypothesis that stock markets react instantly to the news. This study examined ten significant NASDAQ-listed firms using cutting-edge techniques such as latent Dirichlet analysis for Twitter corpus authentication, N-grams, stationary transformations, algorithmic feature selection, and various nonlinear models. Despite differences between businesses, statistically significant causality was shown for various lags. The authors' research led them to a preliminary conclusion that the impact of investor mood on stock prices differs depending on the company. These authors highlighted the importance of using careful processing methods.

According to Bouktif et al. (2020), the body of research on sentiment causality in stock markets is developing quickly. This advancement necessitates the investigation of improved stock market forecasting methods. Although there is evidence that sentiment improves predictability in multivariate data models, its influence seems to depend on contextual characteristics unique to each business, such as the domain, post volumes, or sources. One of the most important factors affecting the outcomes of stock market predictions continues to be the precise portrayal of sentiment signals. Importantly, the knowledge gained from studying stock market forecasting offers hope for other fields attempting to use sentiment signals for causal analysis (Ahmad et al., 2013).

3. Exploring Temporal Sentiment Dynamics: What Insights Can We Gain from Multimodal Data Analysis?

The earliest stages of sentiment analysis heavily rely on the sentiment analysis of textual data from various sources and technologies, including social media platforms, review websites, blogs, forums, and interview transcripts (Birjali et al., 2021). For instance, a recent study in the field of public health examined the temporal trends of emotional swings during the COVID-19 pandemic. In this study, Yu et al. (2021) carefully tracked changes in public opinion over four consecutive months. They divided each day into distinct periods, classified sentiment data, and used heatmap to visualise how emotions changed over the day. In addition, Yu et al. investigated shifts in sentiment in the educational sector by examining how students communicate on public versus private platforms (Yu et al., 2020). To explore sentiment aggregation over specified periods, cutting-edge natural language processing approaches, such as the pretrained bidirectional encoder representations from transformers (BERT) model, were used in their research.

Park et al. (2021) examination of the temporal dynamics of emotional appeals in Russian campaign materials during the 2016 election focused on the political realm. Their research centred on how emotional content in Facebook advertising and Twitter posts affects user perception and online interactions over time. They found new insights into the changing emotional landscape by combining word-level sentiment analysis with natural language processing (NLP).

Another important societal use of temporal sentiment analysis is the early detection of online bullying and suicidal thoughts. Using graph-based data mining techniques, Chatterjee & Das (2020) analyse temporal sentiment in social media data to identify potential risks. Moreover, an algorithm known as automatic contextual analysis and ensemble clustering (ACAEC) was introduced by Sharuee et al. (2021) to analyse sentiment changes over time in product reviews.

Spatial-temporal data mining is a developing field of study that examines sentiment shifts across several regions. Using dictionary-based techniques and machine learning algorithms, researchers such as Ecemis et al. (2021) have employed techniques such as temporal sentiment analysis of socially important locations (TS-SIL) to uncover sentiment trends connected to certain geographic places. To acquire insights into local sentiment dynamics, Hu et al. (2020) investigated local sentiment collected from geo-tweet data.

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Yu He et al. This paper presents a solution to the MuSe-Stress sub challenge in the MuSe 2022 Multimodal Sentiment Analysis Challenge, focusing on predicting physiological arousal and valence based on multimodal data. The authors propose a method called multimodal temporal attention (MMTA) that considers the temporal effects of all modalities on each unimodal branch, enabling interactions between branches and adaptive intermodal balance. The MMTA approach outperforms the baseline system by a large margin on the test set, achieving a concordance correlation coefficient (CCC) of 0.6818 for physiological arousal and 0.6841 for valence.

4. Research Methodology

1. Data Collection: The research methodology involved collecting data from three academic databases: Scopus, the IEEE Xplore Digital Library, and the Wiley Online Library. These databases were selected to ensure a comprehensive overview of sentiment analysis research.
2. Data analysis: The data collected from these databases were analysed in various ways, including by the number of publications, citation analysis, and content analysis. The analysis focuses on sentiment analysis research papers published between 2018 and 2022.
3. Content analysis: The content of sentiment analysis research papers is analysed in terms of the techniques employed, trends in sentiment analysis, and variations in content across the three databases.
4. Comparison: A comparative analysis was conducted to identify similarities and differences in content, technique, and research focus across the Scopus, IEEE, and Wiley databases.
5. Synthesis: The findings from the analysis are synthesised to provide insights into the landscape of sentiment analysis research, including the evolution of techniques, popular methods, and content variations across the selected databases.

Research Questions:

1. Main Research Question:

What is the current state of sentiment analysis research, including the techniques used, trends in sentiment analysis, and variations in content, as observed across Scopus, the IEEE Xplore Digital Library, and the Wiley Online Library from 2018 to 2023?

2. Subsidiary Research Questions:

a. What are the most prominent sentiment analysis techniques used in research papers published in the selected databases during the specified timeframe?

b. How have these sentiment analysis techniques evolved over the years, and what are the emerging trends?

c. Are there variations in the content of sentiment analysis research papers across the Scopus, IEEE, and Wiley databases, and if so, what are the key differences and similarities?

d. What insights can be gained from the comparative analysis of sentiment analysis research across these three databases?

e. What practical considerations and challenges are associated with implementing sentiment analysis techniques in real-world applications, as the reviewed literature indicates?

4.1. What Are the Key Trends and Impactful Contributions in Sentiment Analysis Research Across Prominent Journals?

In our pursuit of comprehensively analysing the landscape of sentiment analysis research, we have focused on three distinguished academic journals: Scopus, IEEE, and Wiley. This selection serves two purposes: first, it provides us with a well-rounded view of the breadth and depth of sentiment analysis research across diverse academic domains; second, it allows us to critically assess the quality and relevance of research contributions in the field. By examining these three prominent platforms, we aim to gain a nuanced understanding of the evolution, trends, and areas of emphasis within sentiment analysis research. This comparative analysis not only helps us navigate the vast sea of available literature but also empowers us to pinpoint high-impact research papers that will enrich our study and contribute significantly to the advancement of sentiment analysis as a field of inquiry.

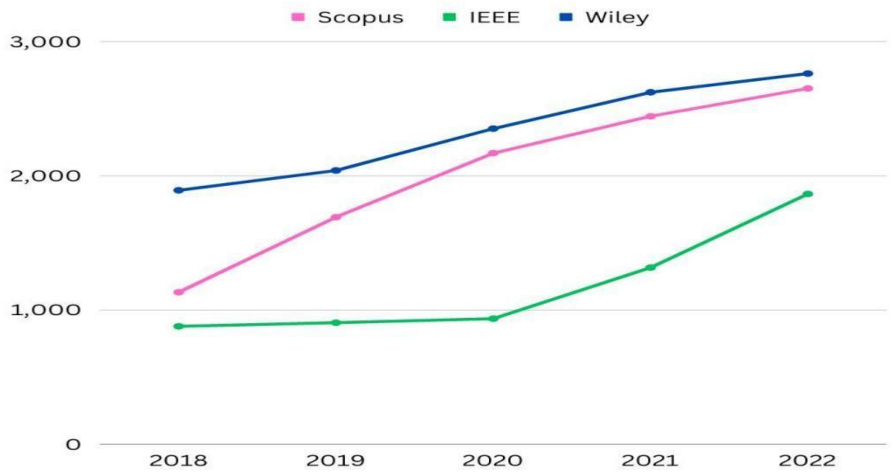

Figure 3 Sentiment analysis in social networks published between 2018 and 2023, according to Scopus, IEEE, and Wiley.

4.1.1. Scopus—A Comprehensive Repository of Sentiment Analysis Research

Within the vast Scopus database, a staggering 27,002 papers are dedicated to sentiment analysis, making it a comprehensive hub for researchers in this field. Of particular interest is the subset of 10,521 papers focusing on sentiment analysis in social media. This extensive research underscores social platforms' pervasive influence on contemporary sentiment analysis inquiries.

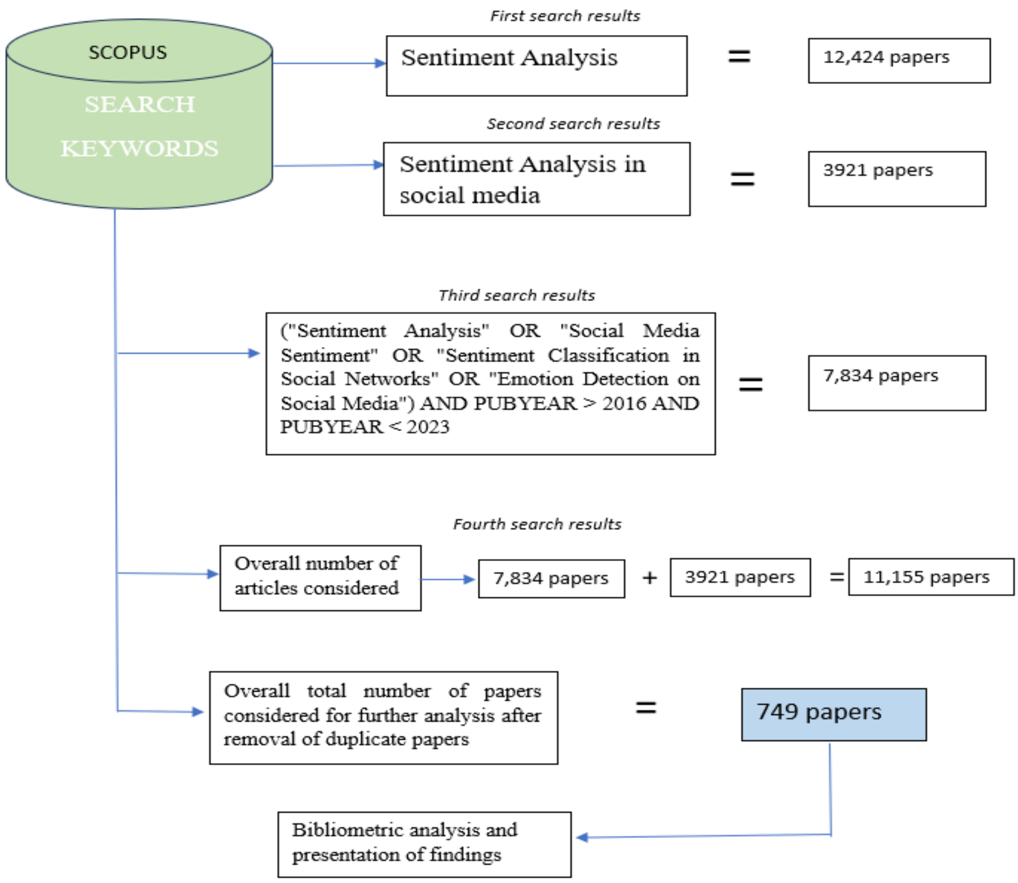

Figure 4 Search strategy used for the Scopus database.

As a multidisciplinary database, Scopus offers researchers a panoramic view of the evolution of sentiment analysis over the years. Contributions to this vast repository span various academic disciplines, including computer science, linguistics, psychology, marketing, and beyond. The sheer quantity of papers, however, necessitates a discerning approach. Researchers must diligently assess the quality, methodological rigour, and relevance of individual papers to ensure the inclusion of high-impact research in their studies.

4.1.2. IEEE - Precision and Depth in Sentiment Analysis

Renowned for its contributions to technology and engineering, IEEE maintains a more focused approach to sentiment analysis within its publications. Among its collection of 12,424 papers on sentiment analysis, 3,921 are dedicated explicitly to sentiment analysis in social media. This focused concentration signifies IEEE's commitment to precision and depth in exploring the applications of sentiment analysis within the technological and engineering domains.

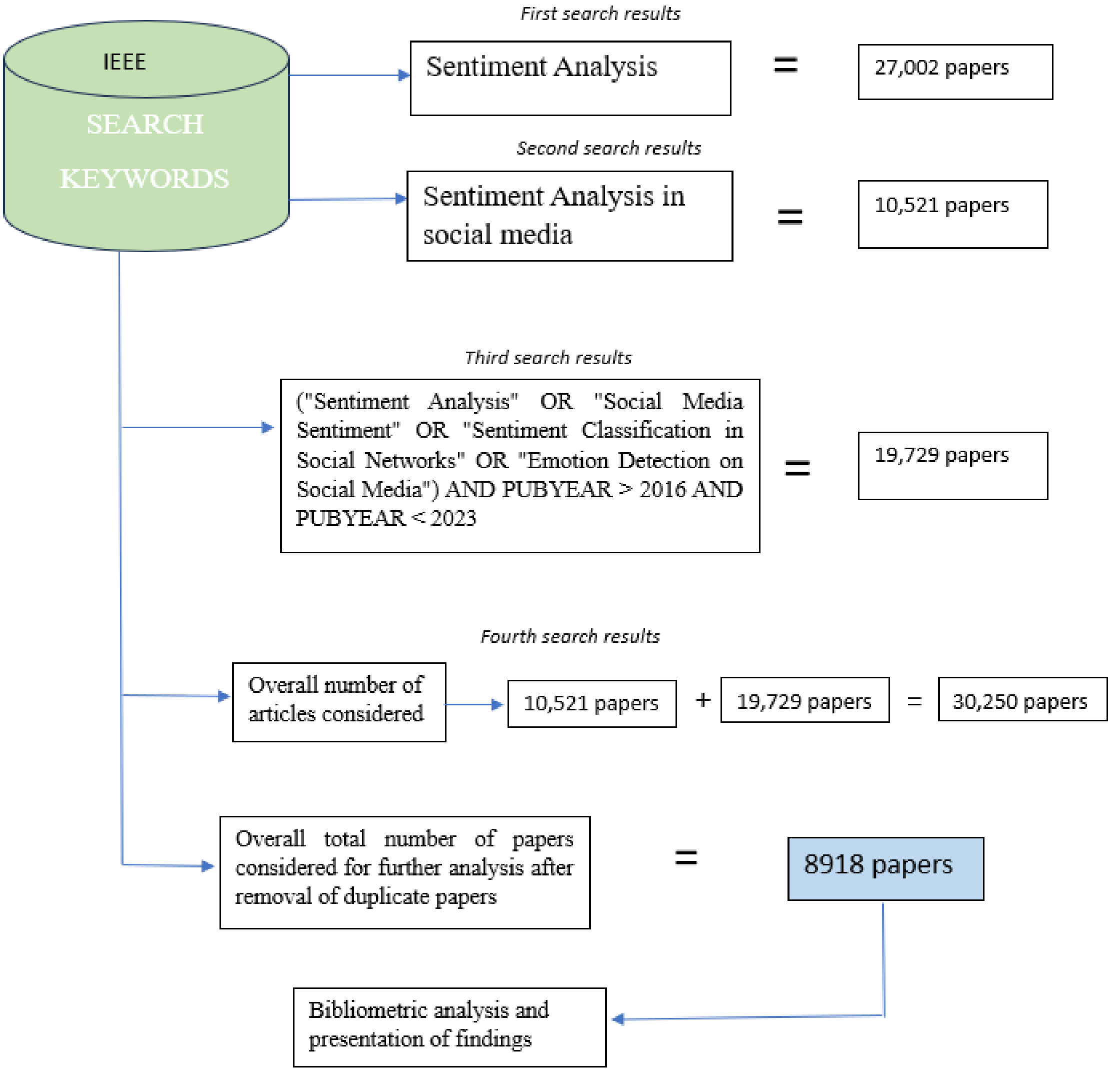

Figure 5 Search strategy used for the IEEE database.

IEEE publications often demonstrate a high degree of technical depth and feature detailed methodologies, algorithmic developments, and rigorous evaluations. Researchers seeking specialised insights into sentiment analysis within technology-driven contexts will find IEEE's contributions particularly valuable. The concentration of sentiment analysis research in the social media sphere further underscores the growing relevance of this field in areas such as opinion mining, sentiment-aware recommender systems, and social network analysis.

4.1.3. Wiley - A Diverse and Inclusive Sentiment Analysis Hub

A renowned publisher, Wiley, hosts a sentiment analysis repository known for its diversity and comprehensiveness. With a substantial total of 35,213 papers, Wiley's collection encompasses a broad spectrum of sentiment analysis research.

Within this extensive repository, 14,999 papers are dedicated to sentiment analysis in social media, highlighting the pivotal role that online discourse and social platforms play in shaping contemporary sentiment analysis inquiries.

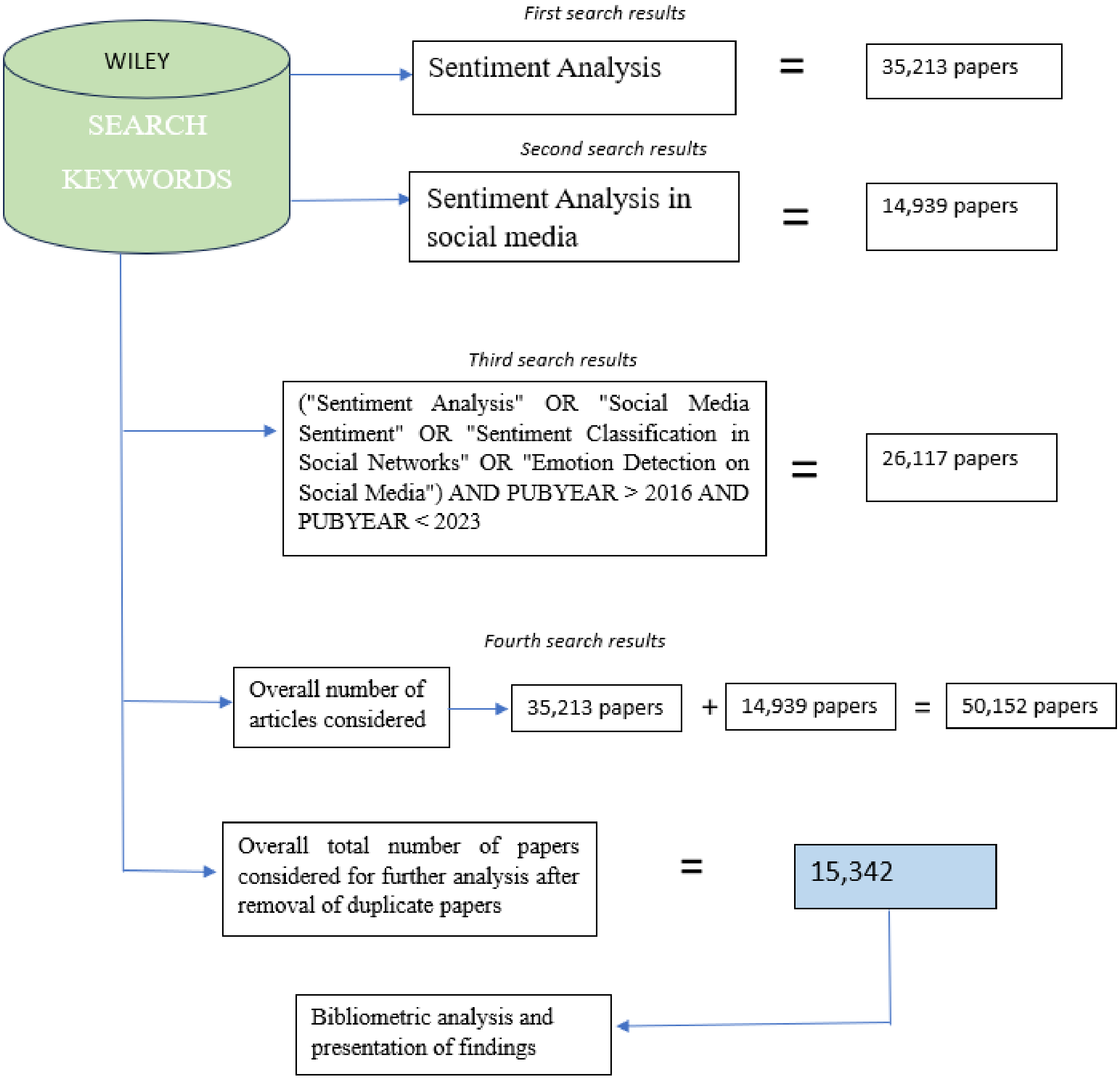

Figure 6 Search strategy used for the Wiley database.

Wiley's inclusive approach welcomes contributions from various academic domains, including computer science, psychology, sociology, economics, and more. This diversity is a testament to the multidisciplinary nature of sentiment analysis research, emphasising its relevance in understanding human behaviour, consumer preferences, and social dynamics. However, the sheer volume of publications within Wiley's repository necessitates meticulous evaluation to discern research of the highest calibre (Gove et al., 2021).

4.2. What Are the Dominant Sentiment Analysis Techniques Across the Scopus, IEEE, and Wiley Databases, and How Do They Influence Research Trends?

4.2.1. Scopus database

In sentiment analysis, the landscape of techniques employed for feature extraction has undergone significant transformations from 2018 to 2022, as evidenced by a comprehensive analysis of publications in the Scopus database. Examining these methodologies reveals intriguing insights into the preferences and effectiveness of various sentiment analysis techniques.

Lexicons, a stalwart in natural language processing (NLP), have consistently held a prominent position in sentiment analysis. These lexical resources are curated databases containing sentiment scores assigned to words or phrases, allowing sentiment analysis systems to assess the emotional tone of the text. Over the years, their enduring relevance has been reaffirmed by citations ranging from 20 to 45, signifying their continued utility in capturing sentiment nuances within textual data (Ahmad et al., 2013).

Alongside lexicons, the adoption of embeddings and transformer-based models, exemplified by BERT, RoBERTa, and BERTweet, has surged, especially in the later years of the observed period. These models revolutionise sentiment analysis by leveraging deep learning and contextual embeddings. They encode words in context, capture intricate sentiment nuances and perform remarkably well in various sentiment analysis tasks. The citation numbers for these models increased from 5 to 60, underscoring their growing prominence and effectiveness in the sentiment analysis community.

Furthermore, traditional techniques such as bag of words, word2vec, N-grams, and tokens remain integral to sentiment analysis. A bag of words represents text as a collection of its constituent words, Word2Vec learns word embeddings that capture semantic meaning, N-Grams analyse sequences of N words, and Tokens represent text units for analysis. Although not as dominant as lexicons or embeddings, these methods provide valuable insights into sentiment classification and sentiment intensity analysis.

Notably, cutting-edge autoregressive and large language models such as T5, T0++, GPT-3, and GPT-J have seen limited adoption in the corpus of evaluated publications. Despite their extraordinary capabilities in various NLP tasks, their relatively sparse presence suggests that practical challenges, computational requirements, or data availability may hinder their widespread application in sentiment analysis.

Regarding processing technologies, prevalent methods include machine learning (ML), deep learning, support vector machines (SVMs), and Bayesian analysis. These techniques consistently feature in the literature during observation, demonstrating their adaptability to sentiment analysis tasks. In addition, albeit to a lesser extent, logistic regression and decision trees occasionally appear in the research landscape.

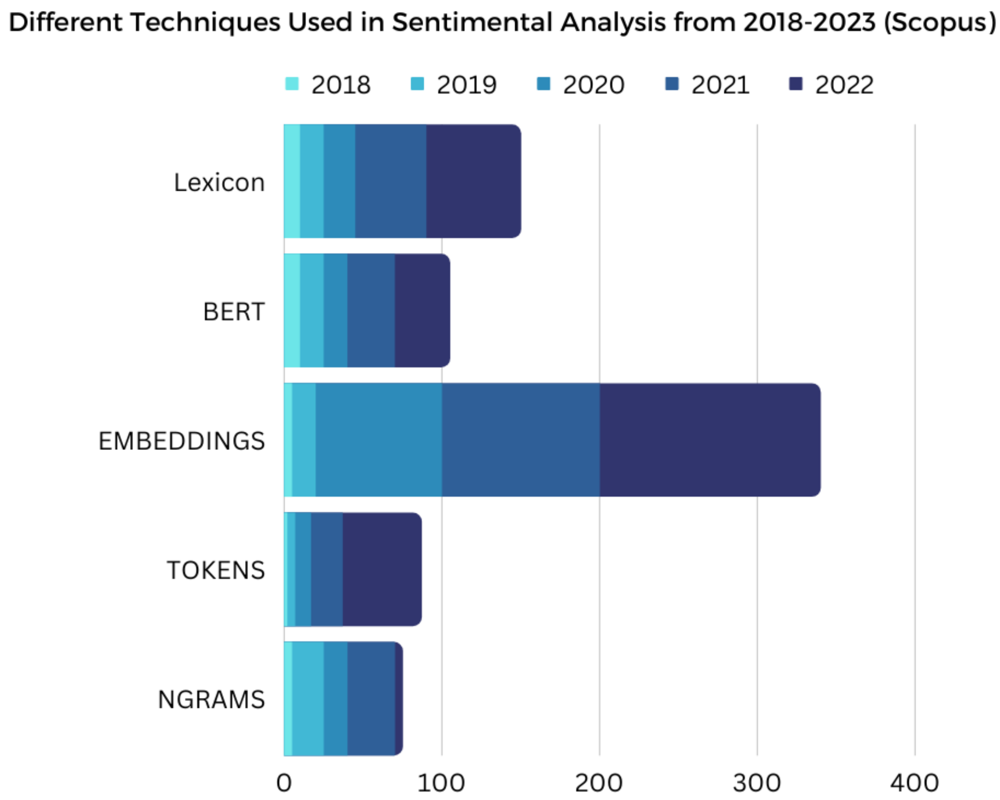

Figure 7 Different techniques used in sentiment analysis from 2018-2023 (Scopus).

However, more specialised methods, such as self-organising maps, causal analysis, or autoencoder methods, are relatively scarce, implying that the sentiment analysis community predominantly relies on established techniques rather than intricate, domain-specific methodologies (Xiaojun et al., 2020).

When scrutinising the breakdown by document type, it becomes apparent that the amalgamation of these techniques broadly characterises sentiment analysis research throughout the period, as revealed by the Scopus database. The diversity of methods and their evolution over time underscore the dynamic nature of this field and the continuous quest for improved sentiment analysis approaches. While lexicons and traditional NLP techniques maintain their importance, newer, context-aware models and deep learning methodologies are progressively shaping the sentiment analysis landscape, promising more accurate and nuanced sentiment assessments in diverse domains and applications (Jian et al., 2023).

4.2.2. IEEE database

In the dynamic field of sentiment analysis, the choice of technique plays a pivotal role in extracting valuable insights from textual data. A comparative analysis of sentiment analysis techniques between IEEE-published papers from 2018 to 2022 and Scopus-published papers revealed intriguing trends and variations in research focus and preferences.

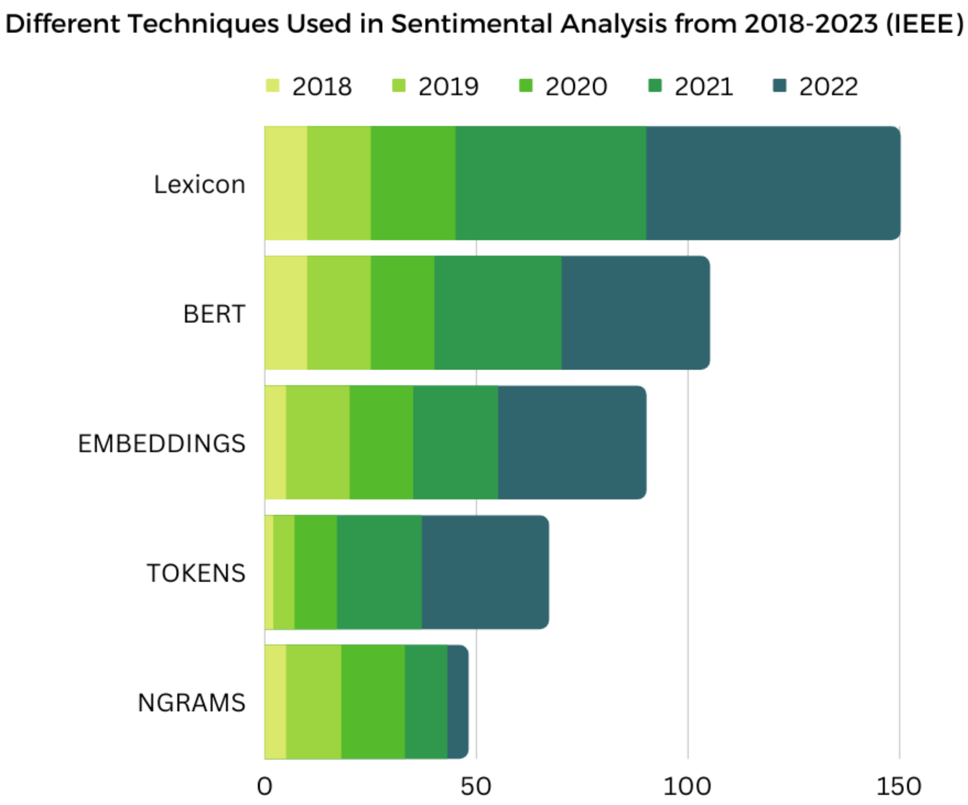

Figure 8 Different techniques used in sentiment analysis from 2018-2023 (IEEE).

Lexicons, which are steadfast and unchanging, constitute a cornerstone of sentiment analysis in both databases. These curated dictionaries provide a foundational reference point for sentiment assessment by associating sentiment scores with individual words or phrases. Whether the research is published in IEEE or Scopus, lexicons remain a reliable resource for determining sentiment polarity. Lexicons are a foundational tool in sentiment analysis. They are curated dictionaries or databases that associate sentiment scores or labels with individual words or phrases. These sentiment scores can indicate whether a word is positive, negative, or neutral in terms of sentiment. Lexicons serve as a reference point for sentiment analysis models to evaluate the emotional tone or sentiment polarity of words within the text. When analysing a document or text snippet, sentiment analysis systems can look up each word in the lexicon to determine its sentiment score and then aggregate these scores to assess the overall sentiment of the text. Lexicons are valuable for tasks such as sentiment classification, where the goal is to classify a text as positive, negative, or neutral based on its sentiments.

BERT (bidirectional encoder representations from transformers), a revolutionary deep learning model, has gained prominence in both datasets, albeit with some nuances in citation numbers. Its ability to consider contextual information from both directions in a sentence has transformed sentiment analysis, allowing for more nuanced and context-aware sentiment assessments. The sustained adoption of BERT underscores its effectiveness in capturing intricate sentiment nuances across different research communities. BERT is a deep learning model based on the Transformer architecture. BERT's ability to consider both the left and right contexts of words in a sentence makes it particularly powerful, allowing it to capture nuanced relationships between words and contextual information. In sentiment analysis, BERT excels at understanding the meaning of words in their surrounding context, enabling it to analyse sentiment in a much more fine-grained and context-aware manner. BERT pretrained models can be fine-tuned for specific sentiment analysis tasks, achieving state-of-the-art performance by capturing the subtleties and nuances of sentiment expression.

Embeddings, which map words to high-dimensional vectors, play a crucial role in understanding sentiment in text. While both databases recognize their importance, there are variations in citation numbers. Word embeddings enable models to discern semantic relationships between words, empowering sentiment analysis systems to effectively comprehend sentiment nuances and contextual meanings. Embeddings, often used in the context of word embeddings such as word2vec or GloVe, are numerical representations of words or phrases. These representations capture the semantic meaning and relationships between words by mapping them to high-dimensional vectors. In sentiment analysis, word embeddings are crucial for understanding text sentiment. Models leverage word embeddings to represent words in a continuous vector space, enabling them to capture semantic similarities and differences between words. This approach is particularly useful for sentiment analysis because it allows models to recognize sentiment-related patterns and associations between words. Word embeddings enable sentiment analysis systems to understand sentiment nuances and the contextual meaning of words in sentences or documents (Yu et al., 2020).

Tokens, representing fundamental text units, have diverse levels of utilisation. IEEE-published papers emphasise token-based sentiment analysis, a method valuable for fine-grained sentiment analysis tasks. Token-based approaches provide detailed insights into sentiment distribution within the text, a capability particularly useful for dissecting complex documents and identifying sentiment nuances. Tokens are fundamental units of text and typically represent words or subwords. Token-based sentiment analysis involves breaking down a text into its constituent tokens and analysing the sentiment of each token individually. This approach is especially useful for fine-grained sentiment analysis, where the goal is to assess the sentiment of individual words or phrases within a text. Token-based methods often assign sentiment scores or labels to each token, and the overall sentiment of the text is determined based on the sentiments of its constituent tokens. Token-based sentiment analysis can provide detailed insights into the sentiment distribution within a document and is valuable for tasks such as aspect-based sentiment analysis, where the focus is on specific aspects or entities mentioned in the text.

N-grams, which capture word sequences, reveal different adoption patterns across the two databases. These sequences help models identify sentiment patterns that emerge from word combinations or phrases, offering a complementary approach to sentiment analysis. N-Gram-based methods are relevant for uncovering sentiment nuances within the text in both IEEE and Scopus publications. N-grams are contiguous sequences of N words or characters within a text. In sentiment analysis, N-Gram-based methods involve analysing the co-occurrence of word sequences to infer sentiment. For example, a bigram (2-grams) might be "very good," which carries a positive sentiment. By examining the frequency and sentiment of N-Grams in a text, sentiment analysis models can predict the overall sentiment expressed in the document. N-gram-based approaches are useful for capturing sentiment patterns that emerge from word combinations or phrases. They can provide valuable insights into sentiment expression in text and are often employed with other sentiment analysis techniques to enhance sentiment classification accuracy (Jian et al., 2023).

These various sentiment analysis techniques cater to different aspects of sentiment analysis, from capturing overall sentiment polarity to assessing sentiment at a fine-grained level within the text. Researchers and practitioners select the most suitable technique or combination of techniques based on their specific sentiment analysis goals and the nature of the textual data they are analysing. Researchers and practitioners must consider these variations in technique utilisation when approaching sentiment analysis tasks. The technique chosen should align with the specific goals of the analysis, whether it involves identifying overall sentiment polarity, understanding sentiment nuances, or conducting fine-grained sentiment assessments. As sentiment analysis continues to evolve, it is essential to remain attuned to emerging methodologies and adapt to the ever-changing landscape of sentiment analysis techniques. The choice of technique can significantly impact the accuracy and granularity of sentiment analysis results.

4.2.3. Wiley database

Lexicons: In the Wiley database, lexicons maintain their significance with citation numbers ranging from 30 to 60, consistent with their importance in sentiment analysis. Wiley-published papers appear to share a similar sentiment analysis technique preference with Scopus, although their citation numbers are notably greater. Lexicons continue to serve as a reliable resource for sentiment assessment in the Wiley dataset, as in Scopus and IEEE.

BERT: BERT has also exhibited steady popularity in the Wiley database, with citations ranging from 30 to 50. This indicates that Wiley-published research has recognized the power of contextual models such as BERT for understanding sentiment nuances, aligning with the trends observed in the Scopus and IEEE databases.

Embeddings: The word embeddings in the Wiley dataset are consistent with those in Scopus and IEEE, with the number of citations ranging from 25 to 50. Word embeddings remain a valuable tool for capturing semantic relationships and sentiment patterns in text across all three databases.

Tokens: Wiley-published papers show a similar trend to that of IEEE papers in token-based sentiment analysis, with citations ranging from 7 to 25. This finding suggested that token-based approaches are more prevalent in Wiley and IEEE than in Scopus.

N-Gram: N-grams also maintain relevance in the Wiley database, with citation numbers ranging from 10 to 30. While N-Gram adoption varies yearly, the continued presence of N-grams reflects their importance in sentiment analysis, as seen in Scopus and IEEE.

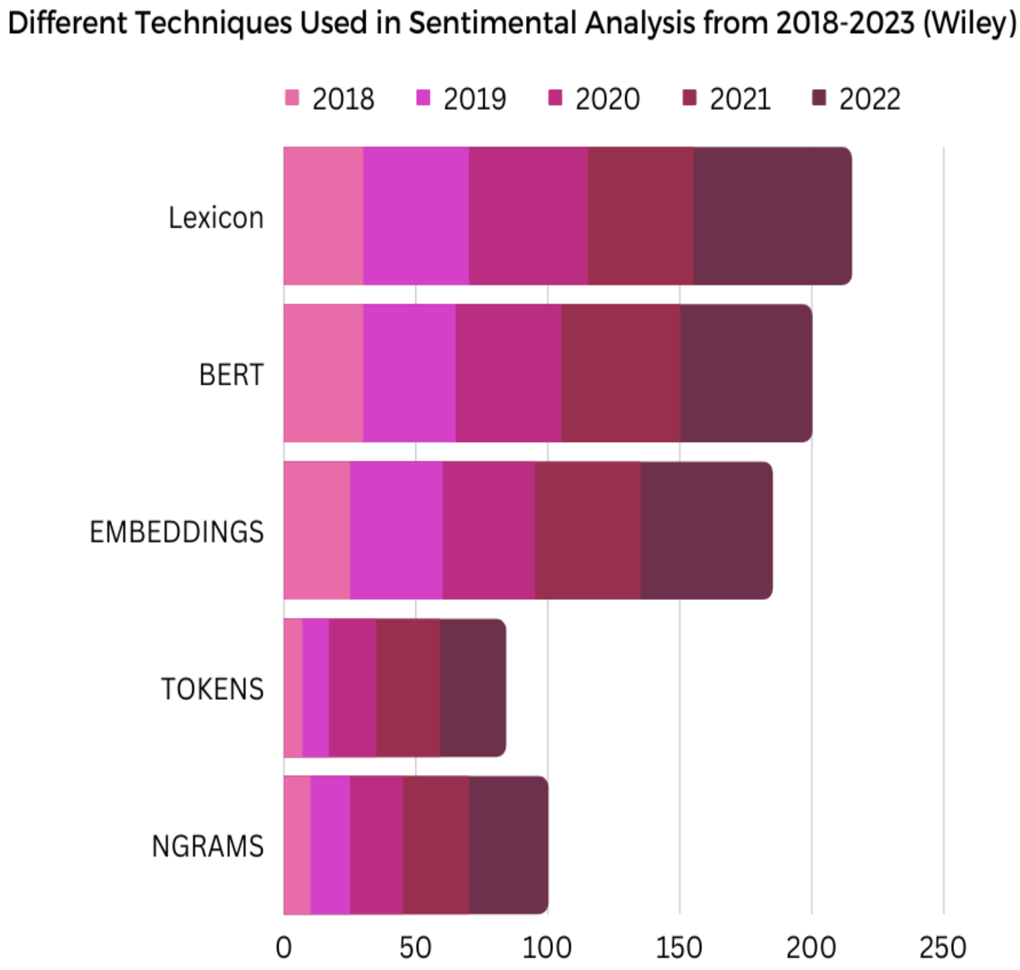

Figure 9 Different techniques used in sentiment analysis from 2018-2023 (Wiley).

Content Variation: The content of Wiley-published research appears to align with both Scopus and IEEE in terms of sentiment analysis techniques and their importance. The key difference lies in citation numbers, which indicate relatively greater engagement and recognition of sentiment analysis methodologies in Wiley publications. This might be due to specific research communities or areas of focus within the Wiley database that emphasise sentiment analysis.

Which database is Better: Determining which database is better depends on various factors, including the specific research objectives and the breadth of the research field. All three databases—Scopus, IEEE, and Wiley—include valuable resources and insights into sentiment analysis. The specific research questions, dataset availability, and research focus should guide the choice of database. Researchers may find it beneficial to explore all three databases to gain a comprehensive understanding of sentiment analysis trends, techniques, and advancements across different academic communities.

In conclusion, Wiley's database shows a pattern of sentiment analysis technique usage similar to that of Scopus and IEEE, with slightly greater citation numbers, but "better" database choice depends on individual research needs. Each database contributes to the collective knowledge in the field of sentiment analysis, offering a diverse range of perspectives and research contributions. Researchers should select the database that aligns most closely with their research objectives and the specific sentiment analysis techniques they wish to explore.

5. How Can Sentiment Analysis Navigate the Complex Terrain of Practical Application and Reproducibility in a Rapidly Evolving Landscape?

The preceding sections have provided a sentiment analysis of intricate tapestry, encompassing analysis, specifically focusing on its applications within the dynamic realm of social networking platforms, exemplified by the ever-popular Twitter platform. Within this expanding field, sentiment analysis offers many distinctive applications, each serving diverse purposes across various sectors, from marketing and policies to health and crisis management. However, despite its growing prominence and relevance, navigating this intricate landscape presents significant challenges for scholars and practitioners alike.

One of the core challenges lies in the sheer diversity of sentiment analysis techniques and methodologies available. Each approach comes with its own advantages and trade-offs, making it a formidable task to select the most appropriate method for a specific situation or task. The relentless pursuit of improved performance measures, often leading to the development of larger and more resource-intensive models, characterises the current research literature. While these cutting-edge models hold promise, they may remain beyond the practical reach of many enterprises due to resource constraints.

Comparing and contrasting various sentiment analysis techniques is further complicated when considering performance criteria alone. The absence of established standards results in these methods being evaluated on different tasks and datasets, rendering direct comparisons daunting. This complexity underscores the pressing need for a comprehensive understanding of the strengths and weaknesses inherent in various strategies.

Our rigorous investigation has unveiled the intricate tapestry of sentiment analysis, encompassing its theoretical underpinnings and real-world implementations. Nevertheless, this endeavour highlights the imperative necessity for further research and analysis to illuminate the path in this complex domain. It is essential to have a profound comprehension of the trade-offs, challenges, and financial implications associated with diverse strategies. This knowledge empowers researchers and practitioners to make well-informed decisions when applying sentiment analysis to their unique objectives and requirements.

The real-world applications of sentiment analysis are vast and continue to expand. However, practicality must be recognized as a critical consideration. Commercial solutions have emerged to help manage, monitor, and analyse published content on social networks. These solutions play a pivotal role in supporting businesses and institutions through leveraging the power of sentiment analysis. However, the journey toward reproducibility and practical applicability is ongoing.

The surge in sentiment analysis-related patents and business applications in social networks underscores the growing need for sentiment analysis in various domains. Commercial entities and academic researchers alike have recognized the potential of sentiment analysis as a tool for understanding human sentiment and opinion on an unprecedented scale. However, the journey toward harnessing this potential is marked by numerous challenges.

Uneven growth is evident across different application fields of social network sentiment analysis. Fields such as marketing and politics have been explored extensively due to data accessibility and the availability of interdisciplinary research teams. However, health and crisis management areas have lagged due to specific knowledge requirements and stringent data protection regulations. Business and economics have also garnered significant attention, driven by the keen interest of commercial entities in tailored solutions for diverse sectors.

Regarding technology adoption, sentiment analysis has shifted from traditional approaches such as lexicons, tokens, Bayesian methods, and bag-of-words techniques to more recent strategies. The emergence of large pretrained models such as BERT, T5, T0++, GPT-3, and GPT-J has introduced the potential for a paradigm shift in sentiment analysis. When combined with zero-shot, one-shot, or few-shot learning, these models can revolutionise sentiment analysis by capturing intricate nuances in sentiment expression (Tanev et al., 2019).

Nevertheless, the adoption of these sophisticated systems is not without challenges. Researchers and practitioners must consider trade-offs, including computing resources, power consumption, inference time, cost, development complexity, and operational factors. The feasibility and applicability of these strategies across diverse domains will continue to be a subject of investigation and adaptation.

In conclusion, sentiment analysis remains a dynamic and evolving field that is poised to play an ever-increasing role in our digital age. To fully unlock its potential, there is a pressing need to bridge the gap between theoretical advancements and real-world utility. This endeavour ensures that sentiment analysis will continue to provide invaluable insights into human sentiment and opinion while addressing the challenges of reproducibility, practical applicability, and technology adoption. The journey ahead promises to be exciting and challenging as sentiment analysis continues to evolve in response to the ever-changing landscape of social networks and human communication.

6. Discussion and Final considerations

In this study, we investigated the recent exponential rise of sentiment analysis within social networks, a trend that is becoming increasingly popular. This ongoing fascination with the area continues despite the release of multiple studies and in-depth review papers (Ashima & Kumar, 2020). There are several reasons for this ongoing interest. First, the field has developed steadily, incorporating new processing methods and branching into several sectors. Second, it struggles with the intrinsic difficulty of quantifying data across diverse domains, as shown by the inconsistent outcomes of research publications using various lexicons (Rodriguez-Ibanez et al., 2021).

Sentiment analysis provides useful insights into the dynamics of emotional states from a temporal viewpoint, especially in fields such as COVID-19 research, advertising, internal school communication, and bullying prevention. Rule-based techniques and lexicons have been used extensively in research on temporal sentiment analysis. A dual-dimensional domain (space-time) where areas can represent particular emotional states has also been made possible through temporal sentiment analysis, showing substantial connections with nontemporal variables such as location.

With the introduction of causation, particularly through Granger causality, temporal analysis has advanced even further. Due to the significant number of publications and the ability of concepts to develop relationships between many factors, the scientific community has shown great interest in these concepts. For example, it has been used to forecast firm stock values based on moods on social media. In this context, the bidirectional relationship between price and sentiment—where immediate signals may foretell price changes and prices may affect sentiment shifts, although on shorter timescales—is an exciting discovery. This shows a causal relationship between these variables, although it is difficult to rigorously determine the direction and force of causality. This research uses linear and nonlinear learning strategies, such as support vector machines (SVMs), latent Dirichlet analysis, and N-grams. Notably, no strategy emerges as being generally appropriate; their effectiveness differs across many businesses and domains. As a result, emotional evidence improves predictability but falls short of fully illuminating the intricate interactions between factors.

Despite the wealth of related research, the variety of methodologies leading to disparate results highlights the enormous opportunity for additional exploration, particularly in particular domains requiring in-depth data handling.

The spike in sentiment analysis-related patents and business applications in social networks demonstrates the increased need for sentiment analysis. Currently, commercial solutions help manage, watch over, and analyse published content on social networks. There are still many opportunities for development in sentiment analysis, both in the academic and commercial realms, as evidenced by the need for more consolidation in the commercial sector and the diverse results from different techniques.

Uneven growth can be seen in social network sentiment analysis application fields. Due to data accessibility and interdisciplinary research teams, marketing and politics are the two most explored fields. However, studies lag in health and crises due to specific knowledge needs and strict data protection regulations. Business and economics have also sparked scholarly writing and scientific research due to the significant interest of commercial entities in specialised solutions for businesses, financial institutions, and government agencies.

In regard to the use of technology, older methods such as lexicons, tokens, Bayesian approaches, and bag-of-words techniques are still used, but more recent approaches such as autoregressive and encoder-decoder transformers are slowly gaining popularity. When combined with zero-shot, one-shot, or few-shot learning models, the rise of large pretrained models such as T5, T0++, GPT-3, and GPT-J heralds a potential paradigm shift in sentiment analysis. A thorough grasp of trade-offs, including computing resources, power consumption, inference time, cost, development complexity, and operational factors, is necessary to use sophisticated systems, such as large language models. It will continue to be difficult to evaluate the feasibility and application of these strategies across various domains without such expertise.

In conclusion, our investigation has several limitations, including the impossibility of replicating all the experiments using new reproducibility methodologies. We have also emphasised the necessity for a more thorough evaluation of commercial technologies and the difficulties presented by temporal causality in sentiment analysis. These findings inspire academics to investigate cutting-edge strategies that address important problems and new challenges in this area by offering insightful information about potential directions for future research.

Ethical considerations

Not applicable.

Conflict of Interest

The authors declare no conflicts of interest.

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