A Review of Chinese Sentiment Analysis:
Subjects, Methods, and Trends

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Abstract

Sentiment analysis has emerged as a prominent research domain within the realm of natural language processing, garnering increasing attention and a growing body of literature. While numerous literature reviews have examined sentiment analysis techniques, methods, topics and applications, there remains a gap in the literature concerning thematic trends and research methodologies in sentiment analysis, particularly in the context of Chinese text. This study addresses this gap by presenting a comprehensive survey dedicated to the progression of research subjects, methods and trends in sentiment analysis of Chinese text. Employing a framework that combines keyword co-occurrence analysis with a sophisticated community detection algorithm, this survey offers a novel perspective on the landscape of Chinese sentiment analysis research. By tracing the interplay between research methodologies and emerging topics over the past two decades, our study not only facilitates a comparative analysis of their correlations but also illuminates evolving patterns, identifying significant hotspots and trends over time for Chinese language text analysis. This invaluable insight provides a roadmap for researchers seeking to navigate the intricate terrain of sentiment analysis within the context of Chinese language. Moreover, this paper extends beyond the academic realm, offering practical insights into sentiment analysis methodologies and themes while pinpointing avenues for future exploration, technical limitations, and directions for sentiment analysis of Chinese text.

1. Introduction

In today's digitally interconnected world, understanding public sentiment and emotions expressed in textual data has become increasingly important [1]. Within the realm of natural language processing (NLP), sentiment analysis stands as a crucial discipline, serving as a linchpin in decoding these nuanced emotions and opinions [2] [3]. Its applications extend across diverse fields including marketing strategies, brand management, social media monitoring, video analysis, and more, offering invaluable insights [4] [5] [6] [7] [8]. The ability to analyze sentiments across languages is especially crucial as the global landscape becomes more diverse and interconnected [9] [10] [11].

Language diversity is an inherent characteristic of global communication, necessitating sentiment analysis techniques that can transcend linguistic barriers [1] [12]. The intricacies of language nuances and cultural variations add layers of complexity to sentiment interpretation [13]. A sentiment-bearing phrase that conveys positivity in one language might carry a different connotation in another [14]. Moreover, cultural norms influence how emotions are expressed, demanding adaptable models that can decipher sentiments within different cultural contexts [15] [16]. Multilingual sentiment analysis [1] [4] [9] [10] [17], the process of assessing emotions and opinions in different languages, addresses this need by enabling a comprehensive understanding of global sentiment trends. With multilingual analysis, we can unveil not only linguistic differences but also cultural nuances and contextual variations in sentiment expressions.

In the realm of multilingual sentiment analysis, the Chinese language holds a significant position due to its extensive usage and the unique challenges it poses [18] [19] [20] [21]. Chinese, with its ideographic writing system, tonal complexities, and rich idiomatic expressions, demands specialized approaches for sentiment analysis [20] [21] [22]. Moreover, given China's influence in global markets and digital spaces, comprehending sentiment within Chinese text is essential for businesses and researchers alike. While existing literature reviews have diligently surveyed these facets, there remains an uncharted territory awaiting exploration: the thematic trends, evolution of research methodologies and topics within the realm of Chinese sentiment analysis.

This study aims to bridge the existing gap by elucidating the distinct evolution of sentiment analysis research methodologies and themes within the realm of Chinese sentiment expression. It addresses this intriguing gap by presenting a comprehensive survey that delves into the dynamic progression of sentiment analysis research methods and thematic foci. While prior literature reviews have expounded upon sentiment analysis techniques, this study takes a pioneering step by specifically examining the interplay between evolving research trends, methodologies and emergent themes, with a particular emphasis on the analysis of sentiment within Chinese text.

This paper is structured to provide a comprehensive review of Chinese sentiment analysis. Section 1 highlights the growing significance of sentiment analysis in understanding public sentiment expressed in textual data, with specific attention to the sentiment analysis within the Chinese language. Section 2 reviews the existing work and underscores the extensive exploration of sentiment analysis, with a focus on the gap in understanding sentiment within the unique linguistic and cultural framework of Chinese text, pointing out there is a need for a pioneering comprehensive survey that examines the evolution of sentiment analysis research methods and themes specifically within the realm of Chinese text. Section 3 provides the detailed survey and analysis on the trends, methods, and topics in sentiment analysis of Chinese text, outlines the evolution of methodologies in multilingual sentiment analysis, especially with a focus on the Chinese language. Section 4 explores the practical applications, limitations, and future prospects of Chinese sentiment analysis. Lastly, Section 5 and section 6 conclude the paper and discusse potential future directions.

2. Background and Importance of This Survey

2.1 Background

Sentiment analysis, a cornerstone of natural language processing, has undergone extensive exploration across a multitude of languages, cultures, and contexts [1] [4] [9] [10]. A growing body of research has shed light on sentiment analysis techniques, methods, and applications, leading to a deeper understanding of human emotions and opinions as conveyed through textual content [5] [6] [7] [8]. However, a critical gap in the existing literature lies in the investigation of sentiment analysis within the distinct linguistic and cultural framework of Chinese text.

Research in sentiment analysis has predominantly focused on the English language, resulting in a comprehensive understanding of sentiment expressions in this English linguistic domain [4][23][24]. Numerous studies have explored lexicon-based approaches, machine learning techniques, and deep learning models for sentiment classification and polarity detection in English text [4] . These efforts have culminated in the development of robust tools and methodologies for deciphering sentiment cues and gauging emotional tone within English textual content [25][26][27] [28] [29] [30].

In contrast, sentiment analysis within the context of Chinese text introduces a host of unique challenges [18] [31] [32] [33]. The rich morphological structure of Chinese characters, combined with the intricate interplay between ideographic meanings, necessitates tailored approaches to sentiment classification [33]. Additionally, the tonal nature of Chinese writing and the reliance on context for accurate sentiment interpretation further complicate the sentiment analysis process [34]. Authors presented a pioneering approach that leverages the modern Chinese pronunciation system, known as pinyin, to enhance Chinese sentiment analysis. By exploring phonetic information extracted from pinyin, including audio clips and pinyin token corpus, the authors developed a novel method to disambiguate intonations and integrate this phonetic information with textual and visual features. Such a approach generated innovative multimodal representations for Chinese words, significantly contributing to the improvement of sentiment analysis in Chinese across various datasets [34].

Chinese sentiment expression often relies on implicit cultural references, idiomatic phrases, and subtle context cues [35]. These intricacies demand a deep understanding of Chinese culture, history, and societal norms to accurately decipher the emotional undercurrents of text. Consequently, sentiment analysis models tailored for Chinese must not only account for linguistic peculiarities but also navigate the intricate web of cultural subtext [36].

A wealth of research in this domain has been dedicated to exploring sentiment analysis specifically in English text, resulting in a plethora of survey papers that comprehensively summarize and analyze the existing methodologies, datasets, and challenges. However, a noticeable discrepancy arises when considering sentiment analysis in the context of Chinese text. Despite the substantial importance of Chinese as one of the world's most widely spoken languages, the literature landscape reveals a distinct lack of comprehensive survey papers addressing sentiment analysis in this linguistic context. While numerous studies have investigated sentiment analysis techniques for Chinese text [14] [37] [38], the scarcity of surveys hampers the consolidation of knowledge and the identification of trends and gaps in this area. This glaring disparity underscores the need for further scholarly endeavors to bridge this gap, providing insights that can guide future research and advancements in Chinese text sentiment analysis. By addressing this imbalance, researchers can contribute to a more inclusive understanding of sentiment analysis across diverse languages and cultures. However, a comprehensive investigation into the evolution of research methodologies and thematic trends within this realm is conspicuously absent.

This paper fills this void by presenting a comprehensive survey that specifically probes the evolution of sentiment analysis research trends, methods, and thematic foci within the context of Chinese text.

This research not only builds upon the foundation of the previous survey paper [4] but also expands its horizons to unravel the intricate tapestry of sentiment analysis within the realm of Chinese text. By employing innovative techniques such as keyword co-occurrence analysis and community detection algorithms, our study not only pioneers an exploration of sentiment analysis within the realm of Chinese but also provides a roadmap for understanding the nuanced interplay between linguistic, cultural, and technological factors in sentiment expression.

2.2. Importance of Chinese Sentiment Analysis

Chinese sentiment analysis remains crucial despite the availability of advanced language models like ChatGPT and other large language models (LLMs) for several reasons:

Language Nuances: Chinese language and sentiments entail unique cultural and linguistic nuances that may not be fully captured by generalized models [39]. Cultural context, idiomatic expressions, and subtle linguistic nuances specific to Chinese language require specialized models for accurate sentiment analysis [40][41][42].

Domain Specificity: Specialized models for Chinese sentiment analysis can cater to industry-specific jargon, domains, and nuances, providing more accurate analysis for various sectors like finance, healthcare, or technology [39][43].

Data Diversity: Chinese sentiment analysis demands diverse and extensive datasets reflecting various dialects, regions, and cultural sentiments within the Chinese language [34] [44]. Specialized models focus on accumulating and understanding this diverse dataset for accurate analysis.

Local Applications: Local applications and platforms in China often require sentiment analysis tailored to the Chinese language [45]. Such applications might demand models that are specifically trained and optimized for local user interactions and content.

Performance Enhancement: While ChatGPT and similar LLMs are powerful, dedicated sentiment analysis models for Chinese can be fine-tuned and optimized specifically for sentiment-related tasks, potentially providing better performance and accuracy for sentiment analysis tasks in the Chinese language context.

While generalized language models like ChatGPT offer significant capabilities, dedicated Chinese sentiment analysis models are essential to address language nuances, cultural specificity, domain requirements, data diversity, local applications, and performance enhancement within the Chinese language sentiment analysis domain.

In addition, China's rise as a global economic leader and its role in initiatives like the Belt and Road highlight its ascent [46][47]. Positioned to become the world's largest economy, China's strategic initiatives, especially the Belt and Road, showcase its influence, shaping global trade, connectivity, and geopolitics significantly.

3. Detailed Survey on Chinese Sentiment Analysis

This section offers an in-depth survey on Chinese sentiment analysis including Data Acquisition of Scientific Publications, Subjects, Methods, Trends, and Hot Topics within the realm of sentiment analysis of Chinese text. It also highlights the progression of methodologies in multilingual sentiment analysis, with a specific emphasis on the Chinese language.

3.1 Data Acquisition of Scientific Publications

In alignment with previous research methodologies [4], this study's data collection involved sourcing research publications from the Web of Science across four primary databases: Conference Proceedings Citation Index – Social Sciences & Humanities (CPCI-SSH), Conference Proceedings Citation Index – Science (CPCI-S), Science Citation Index Expanded (SCI-Expanded), and Social Sciences Citation Index (SSCI). To establish a comprehensive dataset, specific keywords including "sentiment analysis," "sentiment mining," and "sentiment classification" were employed. This targeted keyword-based approach facilitated the identification and extraction of pertinent papers that constituted our data pool. After screening, a total of 711 literature pieces relevant to "Chinese" or the "Chinese language" were identified.

The search spanned from January 2002 to December 2022, encompassing publication types such as "article" and "conference paper". Following the screening process, a total of 711 papers. The distribution of the publications from 2002 to 2022 is shown in Figure 1.

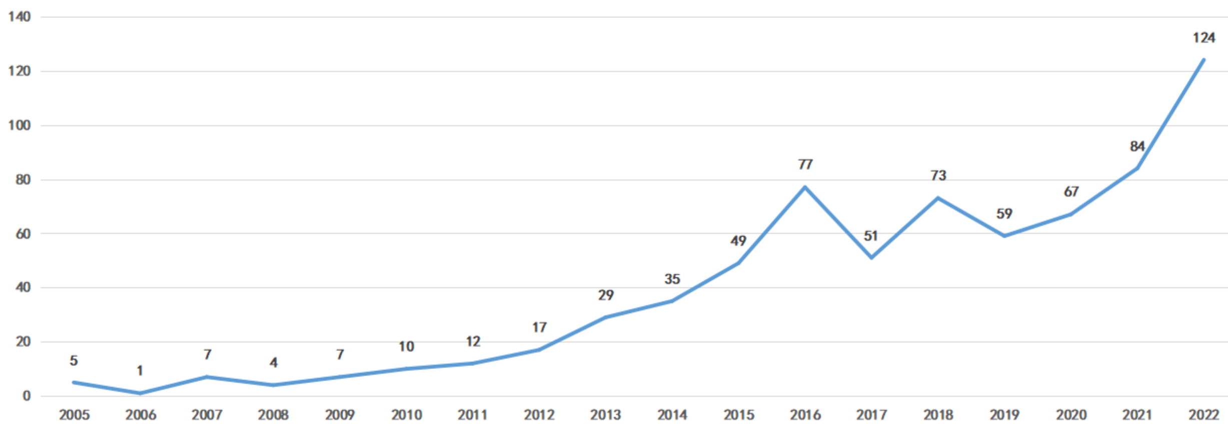


Figure 1 Number of publications related to sentiment analysis in Chinese from 2002 to 2022

Figure 1 illustrates the number of publications in the realm of Chinese sentiment analysis spanning the years 2002 to 2022. Evidently, the publication count follows an exponential growth trajectory over time. The data demonstrates a notable peak in 2016, followed by a minor decline and a subsequent peak in 2018. There is a slight decrease in 2019, after which the count experiences another exponential surge, culminating in the highest point by 2022.

Keywords were extracted from all the collected publications using the same method as previous research [4], in which KeyBERT was used for keyword extraction. Extracted keywords were compared and merged with the original keywords in the publications. Subsequently, merging and screening were conducted, excluding terms like "sentiment analysis," "sentiment classification," "Chinese language," and "Chinese sentiment analysis", which are used as keywords for publication collection. A total of 4,062 keywords were selected with a word frequency of 6,172. Upon observation, keywords with a frequency below 3 were mostly devoid of substantive meaning. Therefore, 258 keywords with a frequency greater than 2 were chosen, totaling 2,025 in frequency, accounting for roughly one-third of the total frequency count. Keywords with a frequency of 10 or more are listed in the table below.

Table 1 Keywords with a Frequency of 10 or More

Keywords	Frequency	Keywords	Frequency
microblog	75	sentiment dictionary	19
deep learning	52	neural network	19
social medium	50	short text	17
text mining	46	Word2vec	17
Natural Language Processing	44	BERT	15
opinion mining	44	Naive Bayes	13
word embedding	43	text classification	13
Chinese text	40	product review	13
sentiment lexicon	40	dimensional sentiment	13
topic model	37	movie review	12
Chinese review	35	feature selection	12
Convolutional Neural Network	35	Latent Dirichlet Allocation	12
SVM	33	feature extraction	11
user review	32	domain sentiment	11
machine learning	31	word vector	11
weibo	31	semantic orientation	10
LSTM	26	hotel review	10
COVID-19	24	semi-supervised learning	10
online review	23	affective computing	10
social network	23	text analysis	10
attention mechanism	22	review sentiment	10
aspect-based	21	semantic	10
text sentiment	20	transfer learning	10

High-frequency keywords often serve as indicators of research focal points. For example, “microblog” is a high-frequency keyword, and it indicates that “microblog” analysis is one important focus for Chinese sentiment analysis. “Deep learning” is also a high-frequency keyword, and it indicates that “deep learning” method is one important focus in Chinese sentiment analysis. Such discoveries is reasonable, and consistent with previous research [48] [49]. We have extracted these prominent keywords to form the foundation for our subsequent analysis.

3.2 Subject Analysis

Table 1 showcases the high-frequency keywords, which essentially encapsulate the primary research focus within the realm of Chinese sentiment analysis. "microblog" and "deep learning" secures the top positions, trailed by " social medium," and " text mining". These high-frequency keywords encompass a wide range, including the study's subject, content, and employed techniques and methods. With these keywords as a foundation, we established a keyword co-occurrence network, effectively visualizing the interplay between research methodologies and subjects.

Using the same drawing approach in [4], the characteristics of this keyword co-occurrence network are elaborated upon in Figure 2. The keyword co-occurrence network characteristics within the six sub-communities described in Table 2. The count of nodes within each community reflects the quantity of keywords represented, while the connections, depicted as links, denote the correlations established among these keywords.

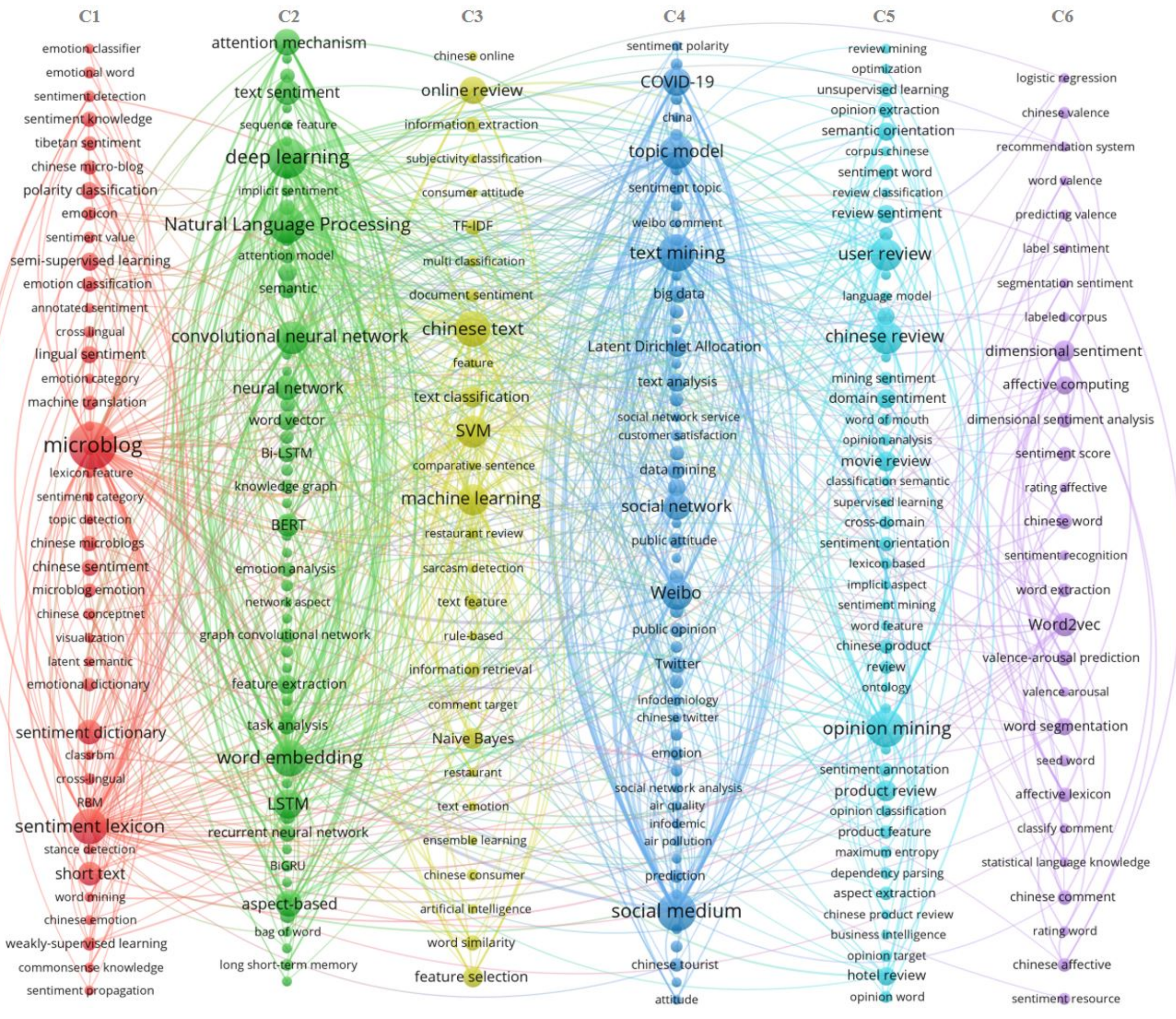


Figure 2 Keyword community network obtained using all the keywords related to sentiment analysis in Chinese text from 2002 to 2022.

Table 2 Network-wide attributes of sub-communities on a global scale.

Community	Connections amongst or within the communities						Nodes
	C1	C2	C3	C4	C5	C6	
C1	116	115	45	99	58	27	41
C2	115	326	102	111	127	55	59
C3	45	102	95	61	66	28	28
C4	99	111	61	262	75	20	55
C5	58	127	66	75	187	38	47
C6	27	55	28	20	38	101	28
Global network							258

Figure 2 shows the keyword community network obtained using all the keywords related to sentiment analysis in Chinese text from 2002 to 2022. C1 community centers on keywords related to Chinese sentiment in the context of "microblog" analysis, like "sentiment lexicon", "sentiment dictionary", "polarity classification" and so on. C2 and C3 communities delve into techniques for sentiment analysis, with C2 community primarily exploring the application of deep learning in NLP, and C3 community focusing predominantly on machine learning approaches and traditional sentiment analysis methods, such as Naive Bayes method, rule-based methods, etc. C4 and C5 communities revolve around specific themes within sentiment analysis. C4 community encompasses subjects linked to "weibo," "COVID-19," and "social medium," while C5 community encompasses topics concerning "user reviews" and "opinions." C6 community encompasses keywords pertinent to various intricacies within the sentiment analysis process, encompassing terms like "sentiment score," "dimensional sentiment," "Word2vec," and "word segmentation."

An intriguing discovery emerges from the comparison with the original keywords "Twitter" in the survey for sentiment analysis of English text [4] [50] [51]: "Twitter" is replaced by "microblog". This substitution appears both logical and congruent with prior research, given that "microblog" predominantly pertains to the Chinese context, whereas "Twitter" is primarily associated with English discourse. This adjustment maintains consistency with previous scholarly undertakings.

Table 2 presents the quantity of nodes denoting keywords within individual communities, along with the corresponding number of interconnecting links. The inter-community linkages highlight robust correlations existing among them. Notably, sub-communities C1, C3, C4, C5, and C6 exhibit significant associations with the C2 community, underscoring a collective emphasis on deep learning methodologies within this research domain. The C2 community has a strong correlation with the C5 community, reflecting the wide application of deep learning methods in the fields of user review and opinion mining. This is consistent with our findings in [4], indicating that researchers are paying more attention to sentiment analysis technology, especially in deep learning methods. The article will analyze the application of sentiment analysis methods in Chinese texts in the next section.

3.3 Method Analysis

Table 3 shows the four main methods of Chinese multilingual sentiment analysis. Categorizing the methods in this way helps provide a high-level understanding of the types of approaches available for sentiment analysis and how they relate to each other. It is worth noting that the boundaries between these categories can sometimes be blurred, as certain methods might incorporate aspects from more than one category.

Table 3: The main categories of the methods

Methods	Characteristics	Merits	Disadvantages
Lexicon-based approaches including rule-based methods [52][53][54][55][56][57][58][59][60][61][62][63][64][65][66][39][67] [68] [69] [70] [71] [72] [73] [74].	Utilize lexicons (lists of words with associated sentiment scores). Assign sentiment scores to words and calculate an overall sentiment score based on the words present in the text. e.g., Lexicon-Based Approaches (e.g., using sentiment lexicons like HowNet, NTUSD, and WordNet) and Rule-based approaches (e.g., defining rules based on linguistic patterns)	Simple to implement, interpretable, can handle domain-specific sentiment, and work well for short texts.	1. Limited Capability for Complex Text Handling: 2. Challenges arise when handling extensive amounts of text data, particularly with sentences and paragraphs. The method might falter in comprehending complex semantic contexts and implicit sentiment expressions within lengthy texts. 3. Difficulty in Capturing Diverse Expressions: The method's coverage of sentiment expressions may be restricted, especially in discerning nuances like sarcasm and contextual variations.
Traditional machine learning algorithms[54][75][76][77][36] [50] [59][78][79][80][81][82][83][84][19][85][86][87][88] [89]	Train supervised traditional machine learning models, e.g., Naive Bayes Classifers, Support Vector Machines (SVM), Decision Trees, Random Forest, etc., using labeled multilingual sentiment datasets.	Can capture complex relationships in data, adaptable to various domains, and suitable for medium-sized datasets	1. Reliance on Annotated Data: The method necessitates labeled training data, which could pose a challenge when acquiring or preparing datasets with accurately annotated sentiments for training purposes. 2. Need for Appropriate Feature Selection: The process requires careful consideration in choosing relevant

			and effective training features. Incorrect or inadequate feature selection might impact the model's performance. 3. Difficulty in Interpreting Sarcasm: The method may struggle to accurately interpret or detect sarcasm, a nuanced form of expression, thereby affecting the precision of sentiment analysis outcomes.
Deep learning models including transfer learning methods [90][91][33][92][33][93][94][95][96][97][98][99][100][31][101] [102] [103] [104]	Utilize deep learning architectures such as Recurrent Neural Networks (RNNs) based methods, and Transformer based models (like BERT) to capture complex patterns in sentiment expression in the text. Fine-tune pre-trained sentiment analysis models on general text in Chinese and other languages. This approach can leverage knowledge from a source language to improve performance in the target language. e.g., Deep Learning Models (e.g., LSTM, CNN) Transfer Learning Methods (e.g., using pre-trained models like BERT, GPT)	Capture sequential patterns in text. Capture contextual information and achieve state-of-the-art performance. Such as Transformer based methods (e.g., BERT, GPT)	1. Necessity for Abundant Annotated Data: Deep learning methods often require substantial volumes of data for effective training, which can be challenging and resource-intensive to obtain or create. 2. High Computational Demands: Deep learning models are known for their computational hunger, often demanding significant processing power and resources, potentially limiting their practicality in resource-constrained environments. 3. Black-box Nature and Lack of Transparency in Decision-Making: These methods often function as black-box models, lacking transparency in how they arrive at conclusions or make predictions, which can hinder interpretability

			and understanding of their inner workings. 4. Difficulty in Handling Out-of-Domain Information: Deep learning models may struggle when confronted with data outside their trained domain, leading to potential inaccuracies or misinterpretations, especially when applied to unfamiliar or diverse datasets.
Hybrid approaches[69][70][76][105][83][74][106][107][108][109][110][22][111][112][45][113][114][115][48][49][116]	Combine multiple methods, such as using a lexicon-based approach to initialize sentiment scores and then fine-tuning using machine learning or deep learning techniques. e.g., Hybrid Approaches (combining the strengths of multiple methods, like lexicon-based and machine learning or deep learning)	Combine strengths of different methods, potentially improving accuracy and robustness.	1. Augmented Complexity in Implementation: Hybrid methods often introduce increased complexity due to the integration of multiple techniques or approaches. This augmented complexity might pose challenges in implementation and understanding. 2. Need for Integration Optimization: Integrating distinct methods within a hybrid framework demands meticulous optimization to ensure seamless cooperation and effectiveness among the combined components. This optimization process can be intricate and time-consuming. 3. Persistence of Individual Method Limitations: Despite their integration, hybrid methods may still retain or inherit limitations from the individual techniques

			or approaches they amalgamate. These limitations could impact the overall performance or efficiency of the hybrid system.

3.3.1. Lexicon-Based Approaches

As shown in Table 3, lexicon-based approaches are rooted in the analysis of individual words and their associated sentiment scores [52][53][54][55][56][57][58]. The lexicon-based approaches include using lexicons and rules for sentiment analysis. These methods leverage sentiment lexicons, which are lists of words with predefined sentiment values, to assign sentiment scores to text. The sentiment lexicons are considered the valuable resources for the sentiment classification task [59] [68]. With the help of lexicons, researchers can analyze the part of speech and emotional tendency of words in the sentences. As can be seen from Figure 2, keywords such as "sentiment lexicon," "sentiment dictionary," "emotional dictionary" in the C1 community have a strong connection with "microblog". Because of the irregular expressions on the microblog, the basic lexicons cannot contain all the meaning or the part of speech of words [66] [70]. Many Out-Of-Vocabulary (OOV) words are commonly used on microblogs, so constructing a new lexicon can help identify phrases (n-grams) more accurately and reduce semantic ambiguity. Some researchers will expand based on dictionaries built by professional organizations [53][60][62][69], while others will build a new dictionary based on the language characteristics of user comments or opinions in specific scenarios[66] [71].

Rule-based approaches, on the other hand, rely on predefined linguistic patterns to determine sentiment. Researchers use sentence dependency analysis, emotional word recognition and other feature extraction to identify sentiment expressions based on predefined word sentiment values or rule templates [52][63][64][72]. If this method can exhaust the rule template as much as possible, it can achieve good sentiment analysis results. However, once encountering irregular large-scale corpus, the limitations of this method will be particularly prominent. In Figure 2, "rule-based" keyword emerges in the C3 community. It reflects that the rule-based method is closely related to the machine learning approaches, and it is more often combined with other methods to improve the sentiment analysis effect [73] [74].

3.3.2. Traditional Machine Learning Algorithms

As more and more users or consumers express their opinions and experiences about products or services online, a large number of comments or opinion texts are in urgent need of sentiment analysis and mining [82] [89]. Lexicon-based methods cannot fully adapt to large amounts of text analysis. Since the accuracy of rule-based methods is relatively poor in the context of big data, traditional machine learning algorithms have been employed for sentiment analysis due to their ability to capture patterns in data without requiring extensive computational resources [89]. Methods like Support Vector Machines, Naive Bayes, Decision Trees, and Random Forest fall into this category. These algorithms use features derived from text data to train models that can distinguish between different sentiment classes. Researchers have studied many text features as the main method to improve the accuracy of sentiment analysis, like TF-IDF[75][87][88], continuous bag-of-words and continuous skip-gram model [86], n-gram [77][88], Word2Vec [84][85], DF value （indicates the frequency of the features in all reviews） [88] and Syntactic, semantic[83], the features of the words with category distinguishing ability and sentiment orientation[76], and so on.

As shown in Figure 2, there are both keywords related to text features (e.g., "feature selection," "TF-IDF," "information extraction") and keywords related to rules (e.g., "rule-based") in the C3 community. Grouping these features and methods together highlights their reliance on algorithmic rules and statistical analysis to make sentiment predictions. However, more research focuses on traditional machine learning, such as "support vector machines (SVM), " and "Naive Bayes.

3.3.3. Deep Learning Models

With the escalating prominence of Web 2.0, microblogging has become integral in our daily lives. Platforms like Weibo facilitate users to freely share reviews and opinions on diverse subjects, including products and events. Leveraging this public opinion data offers valuable insights into societal perspectives. This resource is particularly beneficial for businesses seeking to comprehend user sentiments toward their products, thereby aiding in the development of enhanced offerings [93].

While traditional machine learning models have showcased proficiency in sentiment analysis, their effectiveness dwindles when processing vast volumes of data. This decline in performance often stems from their reliance on feature extraction methods [95]. The brevity of microblog texts restricts feature extraction possibilities. Furthermore, the continuous emergence of new words and extensive network data complicates the extraction and training of text features for traditional machine learning approaches [33].

Deep learning methods present a compelling solution by bypassing manual feature extraction. These models utilize neural networks to autonomously discern intricate patterns and relationships within text data [65]. Their capacity to automatically learn complex patterns alleviates the burden of manual annotation, thereby reducing overall costs associated with sentiment analysis tasks.

As shown in C2 community of Figure 2, evident is the prevalence of deep learning methods surpassing traditional machine learning approaches in sentiment analysis. This C2 community stands out with its extensive network of nodes and connections, indicating its significance of deep learning in the sentiment analysis domain. Notably, keywords from other sub-communities exhibit strong ties to those within the prominent C2 community. Recent advancements have seen a surge in the adoption of deep learning models for sentiment analysis. Researchers have employed diverse models, including but not limited to:

- Long Short-Term Memory (LSTM) [106],
- Tree-LSTM [91],
- Bidirectional Long Short-Term Memory (Bi-LSTM) [117],
- Recursive Neural Deep Model (RNDM) [90],
- Convolutional Neural Networks (CNN) [92][93][95],
- Deep Neural Network (DNN) stacked with Restricted Boltzmann Machine (RBM) layers [33],
- Bidirectional Encoder Representations from Transformers (BERT) [96],
- Gated Alternate Neural Network (GANN) [97]
- Innovative models derived from popular architectures [94][98][99].

Notably, the graph convolutional network (GCN) has gained prominence in recent years due to its ability to encode both graph structures and node features [118]. Its widespread adoption spans various domains within natural language processing, including sentiment analysis [100][101]. Categorizing these models underlines the significance of neural networks in capturing contextual information crucial for understanding subtle sentiment nuances.

3.3.4. Hybrid Approaches

Hybrid methodologies amalgamate different techniques to capitalize on the strengths of various methods, aiming to fortify sentiment analysis accuracy and resilience. Two primary hybrid approaches are prevalent in current research.

One is a combination of lexicon-based approaches and traditional machine learning or deep learning models. For instance:

- Dictionary-Based Hybrid Methods: Researchers like Xu et al. extended sentiment lexicons, integrating them with Naive Bayes (NB) [84], while Wang and Jiang selected informative words combined with Support Vector Machine (SVM) models [76][70].
- Leveraging LDA and HowNet: Fu et al. used Latent Dirichlet Allocation (LDA) for topic identification, employing HowNet for sentiment polarity classification [69]. Similarly, Day et al. extracted multi-feature words from NTUSD, HowNet, and iSGoPaSD, combining them with Bi-LSTM models [106].
- Emotional Dictionary with Neural Networks: Yang et al. merged emotional dictionaries with CNN and attention-based Bidirectional Gated Recurrent Unit (BiGRU) models to develop the SLCABG model [45]. Ahmed et al. crafted domain-specific sentiment dictionaries, integrating them with LSTM models for aspect-level sentiment analysis [114].
- Emotion Identification Based on Rules: Yan et al. identified emotional subjects using rule-based syntactic dependencies, integrating this with SVM models for automatic emotion analysis [74].
- OCC Model Combining Rules and CNN: Wu et al. [113].

Notably, lexicon-based approaches persist as indispensable components in the sentiment analysis process, demonstrating their continual relevance across hybrid methodologies.

The other approach involves merging diverse machine learning models, leading to innovative methods in sentiment analysis. For instance:

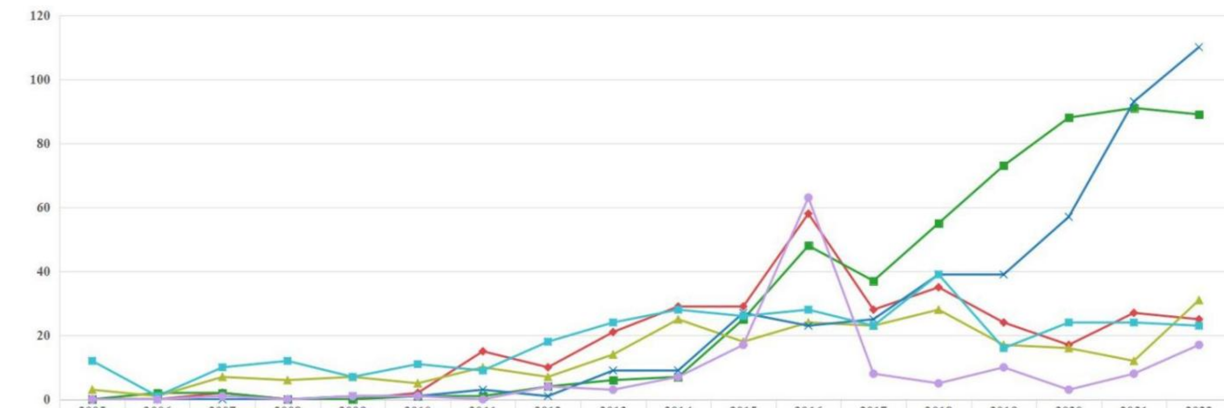
- BT-CNN-ATT Model: Jia developed the BT-CNN-ATT model, amalgamating BERT, CNN, and attention mechanisms. This model not only extracts global features from Weibo contexts but also captures local features, such as words, to effectively mine emotional information [119].
- Bi-LSTM with Multi-head Attention (MHAT): Long et al. explored sentiment analysis of Chinese social media texts by integrating Bi-LSTM networks with the Multi-head Attention (MHAT) mechanism. This fusion aims to address the limitations of traditional machine learning approaches [112].
- Combining CNN with LSTM or Bi-LSTM: Several studies have merged CNN with LSTM [116] or Bi-LSTM [115] models, aiming to enhance the effectiveness of sentiment analysis.

This categorization framework provides a structured understanding of the various approaches used in sentiment analysis. It emphasizes the distinctive traits of each category, elucidating the differences in their principles and methodologies.

The above method classification scheme provides a structured framework for understanding the various methods used in sentiment analysis, highlights the unique characteristics of each category, and helps to clarify how these methods differ in their underlying principles and methodologies.

3.4 Trend Analysis Based on the Number of Keywords

Sections 3.2 and 3.3 delve into the distinct facets of Chinese sentiment analysis research: Subjects and methods. The analysis involves tracking annual shifts in keyword frequency, serving as a reflection of the evolutionary trajectory of research methods and topics within this field [4]. This section leverages the keyword community network (referenced in Figure 2) together with the analysis achievement from Sections 3.2 and 3.3 to quantify the annual word frequency across sub-communities. By discerning fluctuations in the number of keywords over time, these sections aim to elucidate the evolving research trends within the realm of Chinese sentiment analysis. Furthermore, the visual representation of the keyword community's evolution is presented in Figure 3, serving as a graphical aid to complement and illustrate the changes in research trends over the years.



	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
C1	0	0	2	0	0	2	15	10	21	29	29	58	28	35	24	17	27	25
C2	0	2	2	0	0	1	1	4	6	7	25	48	37	55	73	88	91	89
C3	3	1	7	6	7	5	10	7	14	25	18	24	23	28	17	16	12	31
C4	0	0	0	0	1	1	3	1	9	9	27	23	25	39	39	57	93	110
C5	12	1	10	12	7	11	9	18	24	28	26	28	23	39	16	24	24	23
C6	0	0	1	0	1	1	0	4	3	7	17	63	8	5	10	3	8	17

Figure 3 Evolution Diagram of keywords obtained using all the keywords related to sentiment analysis in Chinese text from 2002 to 2022.

To elucidate the evolutionary patterns of keywords within each community throughout the years, we meticulously curated high-frequency keywords representative of each category. The fluctuations in word frequency for these selected keywords across each year were meticulously plotted and are vividly presented in Figures 4 and 5.

Combining the data shown in Figure 3, Figure 4 and Figure 5, we can see that the earliest research mainly started with keywords in the C5 community. Keywords in the C5 community mainly involve "opinion mining," "user review," "Chinese review," etc. The number of keywords has continued to grow over the years, reflecting researchers' focus on mining user opinions and comments. The keywords of the C1 community predominantly revolve around sentiments and emotions related to "microblog," "sentiment lexicon," and "sentiment dictionary". The frequency of keywords has been growing rapidly before 2016, and reached a peak in 2016. It was mainly affected by the "microblog" keyword, and also showed the importance of sentiment-related dictionaries in sentiment analysis. After 2016, the number of keywords has exhibited a declining trend, indicating that scholars' research inclination has shifted towards exploring technology (C2) and specific trending topics (C4). Keywords in the C2 and C3 communities are mainly related to sentiment analysis technology (see Figure 5). The keywords of the C2 community mainly involve words related to deep learning methods such as "Deep learning", "Natural language Processing", "word embedding", "convolutional neural network", "LSTM" and so on. Since 2014, the frequency of keywords has increased significantly, highlighting researchers' high attention to deep learning methods in the field of sentiment analysis. In addition, with the advancement of technology, the granularity of sentiment analysis has gradually changed from document-level and sentence-level to more fine-grained aspect-level[120][121][122][107][123][94][124].

From Figure 5, we can see that the word frequency of "aspect-based" keywords reached the highest in 2022. The C3 community mainly includes keywords related to machine learning and text features such as "machine learning," "SVM," "NB," and "feature selection". The frequency of keywords in the C3 community had been increasing before 2018. However, after 2018, the number of keywords showed a downward trend, reflecting those researchers paid more attention to the application of deep learning methods in sentiment analysis in the C2 community. The keywords of the C4 community mainly involve social media topics related to "Weibo," "social medium," "topic model," and "COVID-19". The number of keywords experienced two significant increases between 2015 and 2020, indicating that researchers are increasingly interested in social media research, especially during COVID-19, with special attention paid to users' emotional expressions on social media during the epidemic[96] [125][126][127]. The C6 community contains keywords related to various complexities in the sentiment analysis process.C6 reached its peak in 2016 in terms of the number of keywords. This is attributed to topics such as "multi-dimensional sentiment analysis," "word segmentation," "affective lexicon," "Word2vec," and "affective computing."

From the perspective of trend analysis, the sentiment analysis of user opinion mining and comments has always been the focus of research. However, in recent years, research topics have gradually tended to explore hot topics on social media platforms, especially Weibo, China's largest social media platform, where the most discussed topic is COVID-19. This is similar to the results obtained from a review of sentiment analysis in English literature, indicating that the world has paid attention to sentiment analysis research on social media platforms in recent years, especially on the topic of COVID-19[4]. In terms of sentiment analysis technology, the focus of research has gradually shifted from machine learning to deep learning, and hybrid methods that can mutually compensate for the shortcomings of the model have also been receiving attention. The conclusion is also similar to our research on English sentiment analysis. However, we found that in Chinese sentiment analysis research, sentiment lexicon and sentiment dictionary have received greater attention than English sentiment analysis research. In addition, the graph convolutional network is gradually applied to the field of sentiment analysis [100][101][128][129]. It reflects the complexity of Chinese text language sentence patterns, word meanings, etc. Integrating lexicons and knowledge graphs into sentiment analysis research can help improve the accuracy of sentiment analysis.

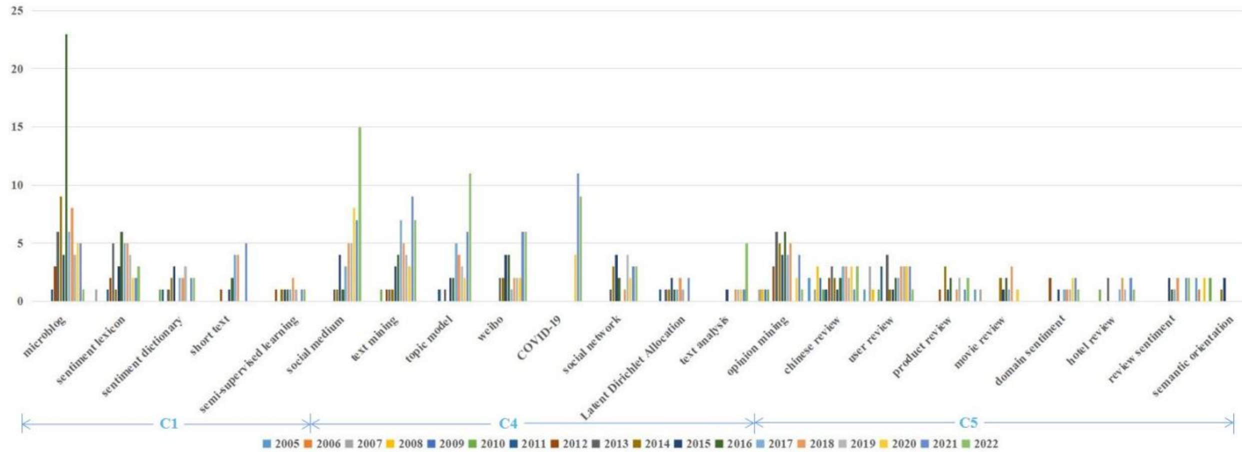


Figure 4 Keyword evolution diagram of C1, C4, and C5 sub-communities

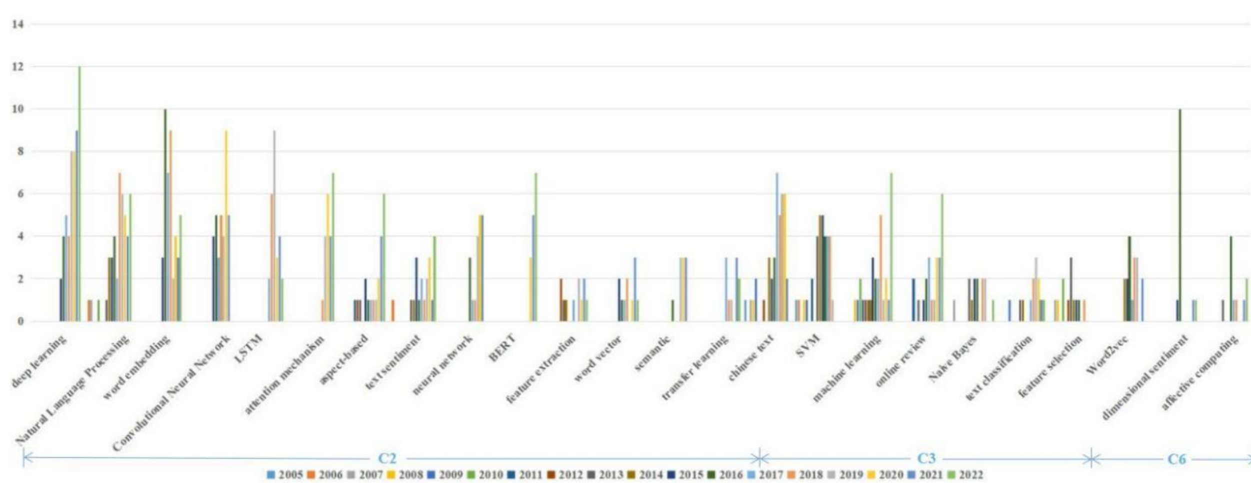


Figure 5 Keyword evolution diagram of C2, C3, and C6 sub-communities

4. Practical Applications and Future Prospects of Chinese Sentiment Analysis

In Section 3, we analyze the themes, methods and trends of existing Chinese sentiment analysis. The practical applications, limitations, and future prospects of Chinese sentiment analysis hold significant implications for industries, communication, and technology.

Despite extensive exploration within existing studies, no publications have explored the use of ChatGPT for sentiment analysis when we conduct this survey research. While there might be such studies available, our search across prominent databases, including the Conference Proceedings Citation Index – Social Sciences & Humanities (CPCI-SSH), Conference Proceedings Citation Index – Science (CPCI-S), Science Citation Index Expanded (SCI-Expanded), and Social Sciences Citation Index (SSCI), yielded no publications related to ChatGPT in this context.

4.1 ChatGPT for Chinese Sentiment Analysis

Language models like ChatGPT can be categorized under the broader category of Deep Learning Models. These models, including transformer-based architectures like ChatGPT, belong to the deep learning category because they leverage neural network architectures with multiple layers to understand and generate human-like text. Deep learning models are known for their ability to capture complex patterns and relationships in data, making them highly suitable for tasks like sentiment analysis.

Among advanced language models, ChatGPT, powered by transformer architectures, has emerged as a versatile tool for sentiment analysis. In a recent breakthrough, GPT-4 showcased remarkable "theory of mind" abilities by effectively tackling 95% of false-belief tasks. This achievement hints at the exciting possibility of GPT-like models evolving to acquire cognitive empathy, potentially revolutionizing their role in understanding human emotions and intentions. ChatGPT is pre-trained on a diverse range of text sources, enabling it to capture linguistic variations, idiomatic expressions, and cultural nuances. Its capacity for transfer learning empowers it to adapt to different languages, including Chinese. ChatGPT's capabilities in multilingual sentiment analysis include:

• Contextual "Understanding": ChatGPT's ability to "understand" context aids sentiment analysis by capturing the meaning behind sentiment-bearing phrases. In a recent study encompassing affective computing tasks, ChatGPT excelled in sentiment analysis, underscoring its prowess in grasping emotional nuances in text [130]. Polgan et al. underscored the pivotal role of ChatGPT in decoding sentiment and emotions, especially in the context of making informed decisions within the ever-evolving specific landscape [131]. With its proficient text analysis capabilities, ChatGPT serves as a valuable tool, equipping users with actionable insights to navigate, gain a deeper understanding of sentiments. Notably, ChatGPT's ability to capture linguistic nuances and adapt to the Chinese sentiment analysis domain positions it as a promising asset for future applications in this field.

• Cross-Lingual Adaptation: The transfer learning approach of ChatGPT enables it to generalize sentiment understanding from one language to another. Previously, Zhang et al. introduced an innovative approach known as hybrid-tuning, aimed at addressing the challenge of catastrophic forgetting [132]. This method seamlessly merges both general and domain-specific knowledge, while also harmonizing the stages of pre-training and fine-tuning. The result is a system that excels in delivering precise and contextually fitting responses within the specific Chinese domain. It is worth noting that such a method holds significant promise for extending its applicability to emerging emotional tasks.

• Handling Idiomatic Expressions: ChatGPT's exposure to a wide array of linguistic contexts equips it to handle idiomatic expressions and nuanced sentiments. For idiom fill-in-the-blank and idiom understanding, Li et al. observed that ChatGPT which provides a straightforward chain-of-thought prompt can enhance performance in intricate reasoning [133].

Amin et al. evaluated the ability of ChatGPT on English affective computing problems, and the results showed that ChatGPT is a good generalist model that can achieve good results on a variety of problems without any professional training[130]. A few studies have also confirmed the feasibility of ChatGPT in the field of Chinese question answering and event extraction [134][135]. The utilization of ChatGPT in a Chinese-centric context for sentiment analysis will be one of the future research directions and applications.

4.2 Global Business Insights

For multinational businesses, understanding sentiment in the Chinese language is invaluable. As the world's most widely spoken language with over 1.4 billion native speakers, Chinese market advantage enables multinational businesses to effectively target Chinese consumers and scale their offerings to a massive population. China's economic influence calls for precise sentiment analysis in a Chinese-Centric context, aiding market strategies and decision-making. In a thorough evaluation using a dataset of 7165 financial questions, Ren et al. found that ChatGPT demonstrated higher levels of professionalism and accuracy compared to human services in Chinese financial conundrums, resulting in increased efficiency, cost savings, and improved customer satisfaction, ultimately enhancing the competitiveness and profitability of financial institutions [136]. Cross-cultural diplomacy is enhanced through accurate sentiment analysis. Chinese-Centric sentiment understanding fosters better cross-border communication, essential for diplomatic relations and cultural exchange. The Chinese market's magnitude makes sentiment analysis pivotal for e-commerce. Chinese-Centric analysis unveils consumer preferences, leading to tailored marketing strategies that resonate with Chinese consumers.

4.3 Enhanced Chinese Language Models

Advancements in Chinese-specific pre-trained models will bolster sentiment analysis accuracy, addressing linguistic intricacies and cultural subtleties. Models like ChatGPT can further adapt to Chinese-specific linguistic nuances, catering to the dynamic expressions of sentiment across regions. Wang et al. exhibited that GPT-4 proficiency on par with Chinese participates who passed the specific exam, demonstrating its potential for discharge summarization, group learning, and strong verbal fluency in human-computer interactions [137]. ChatGPT significantly enhances various capabilities, particularly in Chinese specific task comprehension, while also addressing issues like hallucinations, legal risks, and ethical concerns. This suggests that ChatGPT has the potential to serve as an essential component of the Chinese-Centric sentiment analysis. Besides, creating more labeled data in Chinese is vital for robust sentiment analysis. Hassani et al. explored the potential impact of ChatGPT on data science, presenting opportunities and challenges, that emphasized ChatGPT's role in data augmentation, citing an example where ChatGPT was employed to generate synthetic radiology reports, enhancing the training data for a machine learning model in radiology report classification at the University of California, San Diego [138]. This potentiality has spurred the application of ChatGPT as a means of data augmentation in various interdisciplinary fields. Van Nooten et al. utilized the ChatGPT 3.5 to create authentic anti-vaccination tweets in Dutch, aiming to balance a skewed vaccine hesitancy classification dataset [139]. By augmenting the gold standard data with these generated examples, the study demonstrated notable enhancements for underrepresented classes, overall recall improvement, and a slight decline in precision for more prevalent classes, while also assessing the synthetic data's generalization to human-generated data in the classification task. Collaborative efforts in data augmentation can drive more accurate Chinese-Centric models. Future research should prioritize ethical multilingual sentiment analysis, accounting for cultural sensitivity and fairness in sentiment interpretation.

The fusion of Chinese-Centric sentiment analysis and advanced language models has the potential to revolutionize cross-cultural communication and understanding. As we conclude this exploration, we reflect on the trajectory of sentiment analysis in a globalized world and envision a future where Chinese sentiment analysis paves the way for richer, more accurate cross-lingual emotional assessment.

5. Future Directions

Based on the results of exploring the prospects of Chinese sentiment analysis discussed in sections 3-4, this section outlines several future directions that warrant further exploration.

5.1 Ethical Multilingual Sentiment Analysis and Understanding

Research in multilingual contexts introduces specific ethical challenges related to language dynamics, data handling, and presentation [140]. It is crucial to address these ethical considerations systematically. In the study by Janusch et al., an examination of interviews with Chinese teachers conducted initially in English and later in Chinese highlighted the impact of language dominance on interpretation. The researchers observed that the perspective brought by researchers from another cultural orientation and a position of power can influence interpretation [141]. Switching to Chinese empowered participants, fostering more accurate and expressive communication, resulting in richer, more valid data and robust research outcomes. Holmes et al. recognized the widespread ethical concerns in multilingual research, they advocated for proactive ethical practices, emphasizing the importance of researcher reflexivity [138]. Researchers are encouraged to challenge monolingual state and institutional practices. Therefore, efforts to minimize biases and promote cultural sensitivity in multilingual sentiment analysis will lead to more reliable and universally applicable models. Ethical considerations in model training and deployment are essential for fostering responsible AI development in the future.

5.2 Multilingual Emotion Recognition

Emotion recognition holds a pivotal role in enhancing human-computer interaction. While numerous studies have historically focused on speech emotion recognition utilizing various classifiers and feature extraction methods, the majority have primarily tackled this challenge within the confines of a single language. Numerous studies take a significant leap by expanding monolingual speech emotion recognition to encompass emotions expressed in multiple languages simultaneously, thereby constituting a comprehensive system[142][143]. This departure from the norm represents an exploration into uncharted territory, as the domain of multilingual emotion recognition extends beyond the well-established realm of sentiment analysis. Traditionally, emotions such as joy, sadness, anger, and fear have been explored in the context of single-language studies. However, the current research broadens the scope to comprehend and recognize these emotions across diverse languages. This pioneering approach has the potential to revolutionize human-computer interactions by fostering a more inclusive and culturally sensitive understanding of emotional expressions. By acknowledging and responding to emotions expressed in various languages, this study strives to enhance the effectiveness and adaptability of computer systems, ultimately contributing to a more nuanced and responsive interaction between humans and machines.

5.3. Interpretable Sentiment Understanding

Chinese-centric sentiment analysis involves the identification, examination, quantification, and retrieval of implicit emotions and subject-related information. Its impact spans a wide range of domains, including assessing the mental health of individuals and detecting fraud in the financial sector [144]. As the volume of social media data continues to surge, there is an increasing demand for automated sentiment analysis.

Deep learning, although offering high accuracy, often operates with an opaque decision-making strategy. To bolster decision-making integrity, trust, belief, fairness, reliability, and impartiality become paramount. It is essential to move beyond mere accuracy and address the interpretability of the models. Developing models that not only deliver accurate results but also offer clear explanations for their decisions is crucial for enhancing transparency and accountability in sentiment analysis. This approach ensures that the decision-making process is not only accurate but also comprehensible, fostering trust and confidence in the results generated by sentiment analysis models.

5.4. Fine-Tuning and Domain Adaptation

Analyzing sentiment in Chinese-centric content is essential for extracting user sentiments related to various events or topics, be it in tweets or on Weibo [145][146]. This enables a more nuanced understanding of user sentiments, providing a complementary perspective to sentiment analysis in other languages. While there has been considerable advancement in sentiment analysis technology, there is a noticeable gap in research focusing on Chinese-centric sentiments. To address this gap, future work could involve pretraining models on large-scale datasets specifically for object recognition, laying the groundwork for effective transfer learning. Customizing models for distinct domains and languages through fine-tuning and domain adaptation emerges as a crucial strategy to enhance performance. This approach ensures that sentiment analysis models are attuned to the intricacies of the Chinese language and its unique cultural contexts, ultimately leading to more accurate and contextually relevant sentiment predictions. The exploration of such tailored approaches will contribute significantly to advancing the field of sentiment analysis in the Chinese language.

5.5 Multimodal Understanding

In addition to Chinese-centric textual content, other modalities, such as images and videos, represent straightforward mediums through which individuals express emotions on social networking sites. Social media users are progressively turning to images and videos to articulate opinions and share experiences. Conducting sentiment analysis on this extensive visual content can significantly improve the extraction of user sentiments related to events or topics, creating a complementary aspect to textual sentiment analysis. While substantial advancements have been achieved in this technology, there remains a dearth of research focusing on multi-modal Chinese-centric sentiments. To address this gap, future research could delve into incorporating visual and contextual cues into sentiment analysis models. Recognizing the prevalence of visual content in expressing emotions, integrating these cues can enhance the models' overall understanding of sentiment, leading to more nuanced and accurate predictions. Exploring the multi-modal aspects of sentiment analysis in the Chinese context is imperative to fully grasp the diverse ways in which users convey emotions across different mediums, ultimately advancing the capabilities of sentiment analysis technology in the realm of visual content.

6. Conclusion

In conclusion, this comprehensive survey on the progression of sentiment analysis in Chinese text unveils essential insights into the thematic trends, methodologies, and emerging patterns within this domain. The utilization of a unique framework combining keyword co-occurrence analysis and sophisticated community detection algorithms has illuminated the landscape of Chinese sentiment analysis research.

Throughout the past two decades, this study has traced the dynamic interplay between research methodologies and evolving topics, revealing correlations and shedding light on significant hotspots and trends in Chinese language text analysis. The comparative analysis presented here not only highlights correlations but also signifies evolving patterns, providing invaluable insights into the intricate terrain of sentiment analysis within the Chinese language context.

Our investigation of multilingual sentiment analysis highlights the amplification of challenges in sentiment interpretation due to language diversity. The Chinese language, with its intricate characters and cultural nuances, requires specialized techniques for accurate sentiment assessment. ChatGPT has emerged as a transformative technology, showcasing its adaptability to languages, including Chinese, and its ability to conduct sentiment analysis in context.

Moreover, beyond its academic contribution, this paper serves as a practical guide, offering insights into sentiment analysis methodologies and thematic trends. It lays the groundwork for future explorations, delineates technical limitations, and outlines promising directions for the advancement of sentiment analysis in Chinese text.

The roadmap provided by this study is poised to aid researchers, practitioners, and stakeholders navigating the complexities of sentiment analysis in Chinese language. The identified trends and methodologies serve as a cornerstone for future investigations and advancements in this burgeoning field, fostering continued progress and innovation in sentiment analysis within the context of Chinese text.

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