International Journal of Engineering and Technology, Vol. 15, No. 4, November 2023

A Translanguaging Turn in Sentiment Analysis: Exploring the Role of Language, Culture, and Linguistics in Natural Language Processing

Yanyan Chen*, Li Lin, Zihan Gong, and Wenwen Tan

***Abstract*—Sentiment analysis has witnessed significant advancements particularly in a translanguaging paradigm, emphasizing the entanglement of different languages, modalities, and cultures. This article provides an overview of the translanguaging advances in sentiment analysis, covering techniques, applications, and challenges. The article begins by briefly introducing the major trends of sentiment analysis, highlighting its current importance in understanding and analyzing human emotions and opinions expressed in data. It then delves into the edge-cutting techniques employed in sentiment analysis. Afterwards, the emerging application domains were explored through CiteSpace 5.7.R5. Despite the achievements made in sentiment analysis, numerous challenges persist. The last part of this article presents the challenges and researchers' attempted solutions, which accentuates the need for robust techniques to improve the accuracy and reliability of sentiment analysis.**

***Index Terms*—Sentiment analysis, advances, techniques, applications, challenges**

I. Introduction

Sentiment analysis, a rapidly advancing subfield of natural language processing, focuses on discerning emotions and sentiments predominantly from text data in a specific language. However, as human communication is inherently multilingual, multimodal, and cross-cultural, sentiment analysis must grapple with the emergence of translanguaging [1]. This paradigm shift seeks to enhance the detection of genuine human emotions by accommodating the complexities of multilingual communication. This article seeks to showcase the latest advancements in the field's translanguaging turn, elucidating the rationale for this shift and proposing strategies to realize its objectives.

II. The Need for a Translanguaging Trend in Sentiment Analysis

Translanguaging, as a fundamental characteristic of human communication [2], is increasingly prevalent in today's globalized society. Individuals, with their varied cultural backgrounds encompassing open-mindedness and closed-mindedness, naturally employ a blend of different languages and modalities to express their emotions. Consequently, the manifestation of sentiment can significantly differ across cultures and contexts, as depicted in Fig. 1.

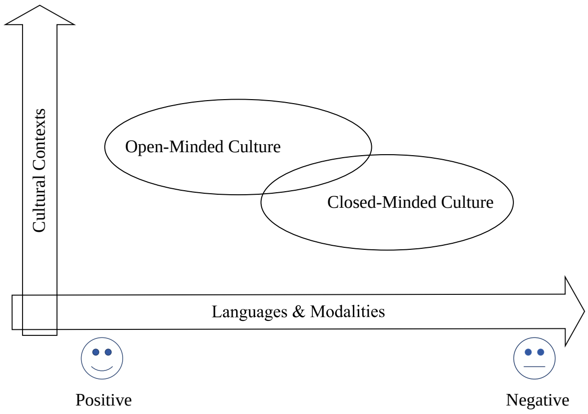

Fig. 1. The translanguaging nature of human communication.

A. Linguistic Implications

Sentiment analysis is based on the interpretation of human language and, therefore, is subject to personal biases, cultural differences, and linguistic variations. The same text can be interpreted differently by different people, leading to inconsistencies in sentiment analysis results.

The way people use language poses significant challenges in sentiment analysis. Sentences that use sarcasm, irony, or figurative language are challenging for sentiment analysis algorithms to interpret accurately. Here are some implications in language use that pose challenges in sentiment analysis:

(1) Irony and sarcasm: Irony and sarcasm are common in language use. People express negative sentiments through irony or sarcasm in a positive way. For example, a person might say, "Great job!" sarcastically, when what they really mean is the opposite. Sentiment analysis algorithms often struggle to recognize such nuances of language [3].

(2) Figurative language: People often use metaphors, similes, and other figurative language to express sentiments. For instance, a metaphor such as "he has a heart of stone" expresses negative sentiment towards an individual. Sentiment analysis algorithms typically struggle with identifying such expressions and might not interpret them correctly.

(3) Ambiguity: Sentences that contain ambiguity lead to conflicting sentiment analysis results [4]. For example, a sentence like "The food was terrible, but the service was great" is ambiguous. The statement expresses the conflicting sentiments, positive and negative affecting the overall sentiment classification.

(4) Connotation: The sentiment expressed in language is not always direct. Words and phrases may have different

Manuscript received August 29, 2023; revised September 25; accepted October 10, 2023.
The authors are with the South China University of Technology, Guangzhou, China.
*Correspondence: flcyy@scut.edu.cn (Y.C.)

DOI: 10.7763/IJET.2023.V15.1243

connotations in different contexts, making it challenging for sentiment analysis algorithms to interpret accurately.

B. Cultural Contexts

Sentiment analysis algorithms have limited contextual understanding, which can lead to inaccurate sentiment classification. For example, sarcasm or irony can be misinterpreted as positive sentiment instead of negative. Currently, cultural differences continue to challenge *sentiment analysis, as studies have shown that people from* different cultures may express sentiments towards the same subject in different ways. For instance, since the Vietnamese language has distinctive characteristics in syntax, structure and expression manner, as in reference [5], researchers examined how Vietnam customers convey emotions and sentiments in their product reviews on social networks, which is under-researched. Furthermore, cultural norms and values influence the polarity and degree of emotional expressiveness, leading to variations in the intensity and frequency of sentiment expressions across cultures.

In terms of sentiment analysis research, efforts to mitigate the impact of cultural differences on sentiment analysis algorithms have also been reported. For example, Wu et al. proposed a cross-lingual sentiment analysis approach that leveraged bilingual corpora to align sentiments across languages [6]. In Ref. [7], a sentiment analysis approach based on context-aware learning was implemented to account for cultural differences in sentiment patterns.

Overall, it appears that cultural differences continue to pose an ongoing challenge to sentiment analysis. However, researchers are exploring various approaches to address this issue and improve the accuracy of sentiment analysis algorithms.

Several cross-cultural theories have been developed to explain how cultural differences impact communication and emotions. One such theory is Hofstede's Cultural Dimensions Theory, which proposes that six dimensions of culture influence behaviours, attitudes, and values across societies. These dimensions include power distance, individualism vs. collectivism, masculinity vs. femininity, uncertainty avoidance, long-term vs. short-term orientation, and indulgence vs. restraint. Another significant theory in cross-cultural research is the Communication Accommodation Theory, which suggests that individuals adjust their communication style to match the cultural norms and values of the person they are communicating with. This theory implies that communication can have an impact on the expression of emotions and sentiments, as individuals may adjust their emotional expression to be more or less intense depending on the cultural context.

Sentiment expression and interpretation can vary significantly across cultures, and this can impact the accuracy of sentiment analysis algorithms.

For example, in some cultures, expressing emotions openly is considered a positive attribute, while in others, it is viewed as unprofessional or inappropriate. Additionally, the interpretation of emotions and sentiments can be affected by cultural norms, values, and communication styles. For instance, individuals from more collectivist cultures tend to express emotions in a more subdued manner than those from individualistic cultures.

Without taking into account cultural factors, sentiment analysis algorithms may produce biased or inaccurate results. Accounting for cultural differences in sentiment expression and interpretation requires an understanding of how different cultural norms and communication styles affect sentiment. Cross-cultural theories provide this understanding, allowing sentiment analysis algorithms to more accurately identify, analyze, and interpret emotions and sentiments across cultures.

C. Multilingual Switching

Sentiment analysis can face difficulties when analyzing text in multiple languages as it requires algorithms that can accurately interpret the nuances of different languages.

Multilingual sentiment analysis involves analyzing the sentiment of a text that is written in multiple languages. This requires the processing of multiple languages, which can present several unique challenges. Here are some challenges in multilingual sentiment analysis:

(1) Language variety: There are thousands of languages spoken worldwide, each with its structure, nuances, and cultural references. It can be challenging to analyze sentiment accurately across different languages, especially when there is a lack of resources and training data.

(2) Translation ambiguity: Translating a text from one language to another can lead to ambiguity in meaning. Sentiment analysis models trained on one language may not perform well when applied to translations, as the use of certain words and expressions may have different connotations in different languages. (3) Cultural differences: Different cultures think and express sentiments differently. A sentiment expressed in one language may not have the same meaning in another language or culture. An understanding of the cultural context in which the sentiment was expressed is crucial for accurate sentiment analysis. (4) Data collection and annotation: Collecting and annotating high-quality data for multiple languages is a challenging and time-consuming task. Often, multilingual data collection is limited by the availability of resources and expertise. [8]

(5) Multilingual integration: Integrating data across languages into a unified sentiment analysis system can be problematic. Integration requires dealing with language differences in data type, structures, and formats.

D. Sentiment Shifting

Sentiment analysis struggles with detecting sentiment shifting over time, especially in dynamic situations, such as real-time social media data tracking.

Sentiment shifting refers to the changes in sentiment over time, which can be difficult to detect accurately. Here are some challenges in detecting sentiment shifting:

(1) Temporal context: Sentiment in a text or conversation can change over time. It can be challenging to understand how the sentiment is changing, what triggered the shift, and when it occurred. The temporal context of the text, such as the time when it was created or received, is crucial for sentiment analysis. [9]

(2) Interpretation of sarcasm and irony: Sentiment analysis algorithms can have difficulty in detecting sarcasm and irony. The sentiment expressed in a text can be the opposite of what is intended, leading to a misinterpretation of the sentiment shift.

(3) Subjectivity: Sentiment analysis is inherently subjective. People have different interpretations and opinions about what constitutes positive and negative sentiment. It is essential to account for these differences to improve the accuracy of sentiment analysis.

(4) Data noise: Sentiment analysis relies on a large volume of data to generate insights. However, the data can be noisy and contain irrelevant and misleading information, which can impact the accuracy of the sentiment analysis results [10].

(5) Domain-specific language: Sentiment analysis algorithms work best when trained on a specific domain or type of language. It becomes challenging to detect sentiment shifting in domains where there is a lack of annotated data.

To overcome these challenges in detecting sentiment shifting, deep learning can be used to improve its accuracy, which can effectively handle temporal context, account for subjectivity, and interpret sarcasm and irony. Pre-processing and cleaning data to eliminate noise could also help. Integrating human expertise into the sentiment analysis process could additionally improve accuracy. Companies should also begin with an understanding of the domain-specific languages used, and use the proper sentiment lexicon for each specific domain to ensure accurate and precise results.

III. Techniques

A. Cross-Lingual Transfer Learning

Transfer learning is a technique that allows models to be trained on one dataset and then applied to another related dataset. This technique has shown promise in sentiment analysis, as models trained on large general corpora can be fine-tuned to perform better on specific sentiment analysis tasks. Transfer learning is used to improve the effectiveness and efficiency of sentiment analysis models by reusing knowledge obtained from pre-training or labelled datasets [11]

Some of the popular techniques used for transfer learning are fine-tuning, multi-task learning, domain adaptation, and cross-lingual transfer learning. Cross-lingual transfer learning is a type of transfer learning that involves transferring knowledge learned from one language to another language. In the context of natural language processing, it refers to the use of pre-trained language models to process text in a target language for which there is limited labelled data or resources.

One way to achieve cross-lingual transfer learning is to use pre-trained language models. These models are trained on large amounts of text data in one language and can then be fine-tuned on a smaller amount of data in the target language. This fine-tuning process allows the model to learn the nuances of the target language and improve its performance on downstream tasks. Another approach to cross-lingual transfer learning is to use parallel corpora, which are texts in two or more languages that are translations of each other. By aligning the parallel texts, models can learn the relationship between words and phrases in the source language and their translations in the target language. This approach can be particularly effective for tasks such as machine translation or cross-lingual information retrieval.

In Ref. [12], researchers have proposed various cross-lingual transfer learning models, including multilingual representations, bilingual models, and zero-shot learning. Multilingual representations involve training a single model on multiple languages to learn a shared representation space. Bilingual models involve training separate models on the source and target languages and then transferring knowledge between them. Zero-shot learning involves training a model on one language and then using it to perform tasks in another language without any additional training data.

In general, cross-lingual transfer learning is a powerful technique for leveraging knowledge across languages and improving the performance of models in low-resource settings. Future research should focus on developing more effective transfer learning methods, particularly for languages with limited resources.

B. Multi-modal Analysis

Multi-modal sentiment analysis involves the integration of multiple sources of information, including text, images, and videos, to perform sentiment analysis [13]. This approach has shown promise in analyzing sentiment in social media and other online platforms. Multi-modal analysis refers to the use of multiple data modalities, such as text, image, and audio, to gain a more complete and informative understanding of a given phenomenon. In sentiment analysis, multi-modal analysis involves the integration of text and other modalities to improve the accuracy and robustness of sentiment classification. Recent advancements in multi-modal analysis for sentiment analysis have shown great potential in improving the accuracy, granularity, and interpretability of sentiment analysis.

One major advancement in multi-modal sentiment analysis is the use of visual information, such as images and videos, in combination with textual data. For example, in the context of social media, users often express their sentiments through images and videos, along with text. Researchers have developed approaches for jointly modelling text and visual features, which have been shown to outperform text-only models in sentiment classification tasks. Moreover, the use of visual information can provide additional insights into sentiment expression, such as facial expressions, gestures, and scene context, that are not captured by text alone.

Another advancement in multi-modal sentiment analysis is the incorporation of acoustic features, such as speech prosody, tone, and pitch, into sentiment classification. This is particularly relevant in the context of spoken language, where non-verbal cues, such as tone of voice, play a crucial role in conveying emotions. Researchers have developed approaches that combine acoustic and textual features, which have been shown to improve the accuracy of sentiment classification in spoken language [14]. Moreover, the use of acoustic features can provide additional information about the speaker’s emotional state, which cannot be inferred from text alone.

The multimodal analysis of text congregated from audio, images, and videos especially shows promise in analyzing sentiment in social media platforms, where users interact with each other through different media types (text, images, and videos). The study proposed a novel approach for multimodal sentiment analysis and the result indicated that this approach improved the understanding of user sentiments and opinions in social media platforms. Chen et al. found that the analysis of the trans-semiotizing between texts and pictures as well as the trans-semiotizing to emojis in social media helped identify online learners' sentiments, which further made learner agency more visible and achievable. In Ref. [15], text, picture, emoji and voice messages in online teacher-student communication were processed through sentiment analysis and the findings indicated that students' emotions were not overwhelmingly negative under crisis conditions. The proper use of these multimodal resources contributed to the maintenance of teacher-student interpersonal relationships.

In conclusion, multi-modal sentiment analysis is an active area of research that holds great promise in improving the accuracy and interpretability of sentiment analysis. Recent advancements have shown that by integrating textual, visual, and acoustic cues, we can gain a more complete understanding of the emotional content in various domains. Future research should focus on developing more effective multi-modal models, particularly in domains with limited labelled data or scarce modalities.

C. Analysis Based on Cognitive Linguistics

The use of cognitive linguistics in sentiment analysis is a relatively new approach as compared to other traditional approaches such as lexicon-based or machine learning-based sentiment analysis. However, cognitive linguistics has been a well-established field of linguistic research for several decades, and its principles have been applied in various natural language processing tasks, including sentiment analysis, for some time now. Researchers are continuously exploring new ways to incorporate cognitive linguistics theories in sentiment analysis to better capture the complex and nuanced nature of human emotions.

According to recent research, cognitive linguistics has emerged as a new approach to sentiment analysis and has been applied to capture the complexity of human emotions. While other traditional approaches such as lexicon-based or machine learning-based sentiment analysis have been widely used, cognitive linguistics provides a new perspective and framework for analyzing sentiment.

Cognitive Linguistics: The sentiment analysis can utilize the cognitive linguistic theoretical approach to incorporate additional features such as metaphors and sentiment expressions (i.e., idiomatic expressions, sarcasm, irony) in a text. By this, we can gain a deeper understanding of sentiments, their context, and their implications.

Social Cognitive Theory: Sentiment analysis can also integrate assumptions from social cognitive theory, which explains how people learn, think, and interact with their environment. In a social environment, individuals express their sentiments and opinions depending on their observations and learning from the environment. By incorporating the social cognitive theory, we can identify and track changes in sentiments, better understand the source of the emotions, and improve the sentiment analysis results.

Liu *et al.* [16] proposed a cognitive computing approach to sentiment analysis that incorporates both linguistic and psychological aspects of human emotions. Traditional and advanced machine-learning algorithms are applied to categorize and capture the context and meaning of words in a text, and evaluated according to performance measures: accuracy, precision, recall and F-Measure. The researchers reported promising results in sentiment classification for textual data. Frasheri *et al.* [17] proposed a model that incorporates the cognitive processes underlying sentiment expression, such as appraisal and affective framing, to handle more complex and nuanced forms of sentiment analysis.

IV. Applications

A translanguaging-sensitive sentiment analysis approach is more applicable to the following fields in the greatest need of this technique. CiteSpace 5.7.R5, a software for data analysis and visualization is used and "category" has been chosen as node type to analyze the application field of sentiment analysis. Web of Science Core Collection was selected as the data source to improve the representativeness and accessibility of the data. The year 2023 was focused because this review is about the advance in sentiment analysis. After searching "Topic Search = 'sentiment analysis' AND 2023", 1392 records are retrieved, including 1226 articles, 96 reviews and 70 proceeding papers. After analyzing these data and visualizing them according to the "centrality", an index indicating the importance of a research field, four major application fields are displayed in Fig. 2 and discussed below: business, environment, economics and society. Since this section concentrates on the application of sentiment analysis in other domains, the nodes relating to the original fields—"computer science" and "engineering, electrical and electronic"—are invisible.

Fig. 2. Category network of "sentiment analysis" in 2023.

A. Business: Customer Analysis

Sentiment analysis has revolutionized the way customer feedback analysis is conducted. In recent years, significant advancements have been made in the field of sentiment analysis, which have made it a more reliable and efficient tool for analyzing customer feedback. The emergence of machine learning algorithms and natural language processing techniques has made it easier to extract valuable insights from customer feedback data. Sentiment analysis is now capable of analyzing complex and contextual language in customer feedback, such as idioms, sarcasm, and subtle nuances that a human analyst might miss.

One recent advancement in sentiment analysis is the use of deep learning models such as neural networks and Convolutional Neural Networks (CNNs). These models can analyze customer feedback data at a granular level, enabling them to identify specific topics and themes that customers are talking about in their feedback. This enables businesses to understand not just the overall sentiment of their customers, but also the specific pain points and areas for improvement that customers are highlighting. This can be used for targeted improvements in customer service and product development.

Another recent advancement in sentiment analysis is the integration of sentiment analysis with other analysis techniques, such as topic modelling and emotion detection. This integration enables businesses to understand how different aspects of their products or services are perceived by customers and the emotions that are associated with those perceptions. [18] Combining sentiment analysis with other techniques also helps to reduce false positives and negatives, which enhances the accuracy of customer feedback analysis. As a result, businesses can understand real-time feedback from customers and act accordingly.

B. Environment: Opinion Analysis

Sentiment analysis in the environmental field refers to the application of Natural Language Processing (NLP) techniques to analyze and determine the sentiment or opinion expressed in textual data related to environmental issues. It involves assessing whether the expressed sentiment is positive, negative, or neutral toward specific environmental topics, initiatives, policies, or events.

(1) Natural Disaster Analysis: Sentiment analysis can be used to analyze social media posts, tweets, or comments related to natural disasters. It helps in monitoring public sentiment during and after catastrophic events, allowing authorities and relief organizations to gauge the emotional state of affected individuals, identify urgent needs, and tailor their responses accordingly.

(2) Public Perception of Energy Sources: In the realm of energy analysis, sentiment analysis proves instrumental in assessing public sentiment regarding diverse energy sources, encompassing fossil fuels, renewable energy, nuclear energy, and alternative fuels. This analytical approach facilitates the comprehension of prevailing public opinions, concerns, and levels of acceptance towards the myriad energy options, thereby assisting policymakers and energy enterprises in their decision-making endeavors. [19]

(3) Urgent Policy Evaluation: The application of sentiment analysis enables the assessment of public sentiment concerning some COVID-19 policies, regulations, and governmental responses. Through this analysis, insights are gained into public acceptance, concerns, or resistance regarding various measures, including lockdowns, mask mandates, travel restrictions, and vaccination campaigns. Such information proves valuable to policymakers, assisting them in refining strategies and effectively addressing public concerns.

(4) Perception of Biodiversity and Ecosystems: The application of sentiment analysis enables the examination of sentiments expressed concerning biodiversity conservation and the significance of ecosystems, facilitating the identification of prevailing attitudes towards the preservation of natural habitats, the protection of endangered species, and the comprehension of the intrinsic value of ecological diversity.

By performing sentiment analysis in the environmental domain, researchers, organizations, and policymakers can gain insights into public opinions, attitudes, and emotions toward environmental issues, ultimately contributing to effective environmental management and sustainability.

C. Society: Crisis Analysis

Sentiment analysis has gained significant attention in the area of crisis management because it can provide important insights into the emotions and opinions of people during a crisis. By monitoring social media data and news sources in real-time, sentiment analysis can help crisis management teams respond quickly and effectively to an emergency.

One recent advance in sentiment analysis for crisis management is the use of machine learning algorithms that can detect and classify specific emotions such as anger, fear, and sadness. This can help crisis management teams to identify high-risk populations that may require special assistance and provide targeted interventions [20]. In addition, machine learning algorithms can learn from past crises and improve their accuracy over time.

Another advance in sentiment analysis for crisis management is the integration of geolocation data [21]. By combining sentiment analysis with location data, crisis management teams can identify emerging hotspots and direct resources where they are needed most. This can also help teams to track the movements of people during a crisis and provide important information to first responders.

Sentiment analysis can also be used to predict future trends and anticipate potential crises. By analyzing historical data and social media posts, machine learning algorithms can identify patterns and trends that may indicate a crisis in the making. This can help crisis management teams to take a proactive approach and respond before the situation escalates.

V. Conclusion

The translanguaging turn represents a significant advancement in the field of sentiment analysis, as it offers a closer approximation to human sentiment expression. This paradigm encompasses a multidisciplinary approach that incorporates linguistics, psychology, and sociology to delve into the underlying cognitive and social mechanisms of sentiment expression. By recognizing the importance of understanding human emotions within authentic communicative settings, the translanguaging trend in sentiment analysis reflects a paradigm shift that places emphasis on comprehending the intricate cognitive and social factors that shape sentiment. This approach acknowledges that sentiment is not solely determined by individual psychology, but is also influenced by broader societal and cultural factors. As a result, this paradigm advocates for a more nuanced and contextually-grounded analysis, allowing for a more comprehensive understanding of human emotion in diverse linguistic and cultural contexts.

Conflict of Interest

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Y.C. conceptualized the article, wrote the first draft and supervised the research and writing process; L.L. collected and analyzed the data through Citespace and wrote the results of the data analysis as well as the content of Section IV; Z.G. managed the data collection process, clean the data before data analysis, assisted the data analysis and re-wrote the conclusion; W.T. reviewed and copy-edited the article. All authors had approved the final version.

FUNDING

This work was supported by Guangdong Philosophy and Social Sciences Planning Office of China, Grant Number GD23CWY07.

REFERENCES

[1] Y. Chen, P. Zhang, and L. Huang, "Translanguaging/trans-semiotizing in teacher-learner interactions on social media: Making learner agency visible and achievable," *System*, vol. 104, pp. 1–13, 2022.

[2] W. Li, "Translanguaging as a practical theory of language," *Applied Linguistics*, vol. 39, no. 1, pp. 9–30. 2018. https://doi.org/10.1093/applin/amx039

[3] A. Rahma, S. S. Azab, and A. A. Mohammed, "Comprehensive survey on Arabic sarcasm detection: Approaches, challenges and future trends," *IEEE Access*, vol. 11, pp. 18261–18280, 2023. doi: 10.1109/access.2023.3247427

[4] F. Yin, Y. Wang, J. Liu, and L. Lin, "The construction of sentiment lexicon based on context-dependent part-of-speech chunks for semantic disambiguation," *IEEE Access*, vol. 8, pp. 63359–63367, 2020. doi: 10.1109/access.2020.2984284

[5] N. Truong, T. T. Nguyen, and T. L. Luong, "Extracting aspects in product reviews of Vietnamese e-Commerce websites," *International Journal of Computer Science and Network Security*, vol. 20, no. 11, pp. 89–95, 2020. doi: 10.22937/IJCSNS.2020.20.11.11

[6] H. Wu, Z. Wang, F. Qing, and S. Li, "Reinforced Transformer with cross-lingual distillation for cross-lingual aspect sentiment classification," *Electronics*, vol. 10, no. 3, pp. 1–14, 2021. doi: 10.3390/electronics10030270

[7] H. Elfaik and E. H. Nfaoui, "Combining context-aware embeddings and an attentional deep learning model for arabic affect analysis on Twitter," *IEEE Access*, vol. 9, pp. 111214–111230, 2021. doi: 10.1109/access.2021.3102087

[8] Y. Zhang, Z. Cao, D. Ji, and L. Li, "A hybrid model based on neural networks for social emotion detection in text," *IEEE Access*, vol. 7, pp. 30082–30091, 2019. doi: 10.1109/access.2019.2900289

[9] L. Xu, Q. Yan, and X. Cheng, "A context-specific co-training framework for multimodal sentiment analysis," *ACM Transactions on Internet Technology*, vol. 21, no. 2, pp. 1–23, 2021. doi: 10.1145/3427393

[10] N. A. Bakar, Z. M. Kasirun, N. Salleh, H. A. Jalab, "Polarity lexicons: A comparative study on arabic sentiment analysis," *IEEE Access*, vol. 8, pp. 28112–28122, 2020. doi: 10.1109/access.2020.2978022

[11] R. Sweidan, M. N. Al-Kabi, I. Alsmadi, and H. Wahsheh, "Arabic sentiment analysis: Corpus-based and lexicon-based," *Applied Computing and Informatics*, vol. 14, no. 1, pp. 58–70. 2018. doi: 10.1016/j.aci.2015.03.001

[12] M. Al-Smadi, O. Qawasmeh, M. Al-Ayyoub, and Y. Jararweh, "Deep recurrent neural network vs. support vector machine for aspect-based sentiment analysis of Arabic hotels' reviews," *Journal of Computational Science*, vol. 28, pp. 168–179, 2018. doi: 10.1016/j.jocs.2018.03.017

[13] J. Wu, T. Zhu, X. Zheng, and C. Wang, "Multi-modal sentiment analysis based on interactive attention mechanism," *Applied Sciences*, vol. 12, no. 16, pp. 1–10, 2022. doi: 10.3390/app12168174

[14] J. Chen, C. Sun, S. Zhang, and J. Zeng, "Cross-modal dynamic sentiment annotation for speech sentiment analysis," *Computers and Electrical Engineering*, vol. 106, pp. 1–14, 2023. doi: 10.1016/j.compeleceng.2023.108598

[15] R. Al-Zaidy and M. Carpuat, "Simpler and smaller: making BERT for parallelism identification easier to train and use," in *Proc. the 2019 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, Hong Kong, China, 2019, pp. 4305–4310

[16] B. Liu, L. Wang, and H. Jin, "New advances and challenges of cooperative multi-agent systems," *Neurocomputing*, vol. 481, pp. 32–47, 2022. doi: 10.1016/j.neucom.2021.02.063

[17] M. Frasheri, V. Papaspyros, Z. Doulgeri, and L. Nalpantidis, "A survey of multi-robot human-robot interaction," *Information Fusion*, vol. 78, pp. 120–136, 2023. doi: 10.1016/j.inffus.2021.11.010

[18] M. Malik and Y. Kumar, "A comprehensive study on Internet of Things (IoT) and its applications in smart agriculture," *Journal of Ambient Intelligence and Humanized Computing*, 2023. doi: 10.1007/s12652-023-03379-5

[19] P. Brusilovsky and C. Peylo, "Adaptive and intelligent web-based educational systems," *International Journal of Artificial Intelligence in Education*, vol. 13, no. 2–4, pp. 159–172, 2022. doi: 10.1023/A:1022100409476

[20] H. Wang, M. Ouyang, L. Wang, C. Lu, Z. Xu, and G. Min, "The role of new technologies for smart city in China," *IEEE Access*, vol. 6, pp. 13084–13093, 2022. doi: 10.1109/ACCESS.2018.2800438.

[21] Y. Yuan, F. Wang, X. Li, Y. Liu, L. Xu, and S. Wang, "A dynamic migration execution strategy for edge computing based on reinforcement learning," *Future Generation Computer Systems*, vol. 134, pp. 1–11, 2023. doi: 10.1016/j.future.2022.111513