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Application of Sentiment Analysis as an Innovative Approach to Policy Making: A Review

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***Abstract*—This literature review comprehensively explains the role of sentiment analysis as a policymaking solution in companies, organizations, and individuals. The issue at hand is how sentiment analysis can be effectively applied in decision making. The solution is to integrate sentiment analysis with the latest NLP trends. The contribution of this research is the assessment of 100-200 recent studies in the period 2020-2024 with a sample of more than 5,000 data, as well as the impact of the resulting policy recommendations. The methods used include evaluation of techniques such as Deep Learning, lexicon-based, and Machine Learning, using evaluation matrices such as F1-score, precision, recall, and accuracy. The results showed that Deep Learning techniques achieved an average accuracy of 93.04%, followed by lexicon-based approaches with 88.3% accuracy and Machine Learning with 83.58% accuracy. The findings also highlight the importance of data privacy and algorithmic bias in supporting more responsive and data-driven policymaking. In conclusion, sentiment analysis is reliable in areas such as e-commerce, healthcare, education, and social media for policy-making recommendations. However, special attention should be paid to challenges such as language differences, data bias, and context ambiguity which can be addressed with models such as mBERT, model auditing, and proper tokenization.**

***Keywords*—Recommendation; Policy; Quality; Sentiment Analysis.**

I. Introduction

Data on research libraries shows that Sentiment Analysis is one of the most researched topics, as evidenced by more than 80,000 studies on the ScienceDirect and ACM Digital Library platforms, 69,400 studies on Google Scholar and more than 10,000 studies on SpringerLink and IEEE Xplore. Sentiment analysis is an important component of NLP that is widely used with the aim of identifying and evaluating emotions [1], feelings or mood conveyed [2], point of view, reflection of thoughts, and perspectives so as to divide them into positive, neutral, or negative classes [3].

There are many things that use the sentiment analysis approach as one of the options for policy making [4][5], both in economics [6] such as the application of sentiment market analysis using macro-economic variables [7], ecommerce [8] such as the application of Shopee application sentiment review [9], financial [10] such as the application of market sentiment and stock market return [11], health [12] such as the application of health care service recommendations [13], education [14] such as the application of analyzing the impact of education to age on investor sentiment [15], and political [16] such as the application of analyzing public sentiment towards the Nigerian presidential election [17]. This is what makes sentiment analysis widely used in various sectors as an evaluation material for policy makers such as survey institutions, political and government academics, political candidates and their winning teams, political parties [18], health institutions, government, companies, and even individuals. Sentiment analysis provides important insights for decision-making in various sectors. Governments can adjust policies and identify problems early, while businesses understand consumer perceptions to improve marketing and services. In the healthcare sector, it captures patient concerns, and the media measures the impact of campaigns. Challenges such as hidden dissatisfaction and crisis response can be addressed quickly, making sentiment analysis essential for various domains.

In practice, the sentiment analysis approach requires data as a source of information that can be managed. The data used as material in the sentiment analysis approach is usually in the form of data derived from stakeholders in order to be able to make accurate decisions. Data used such as customer data [19][20], investor data [21][22], user data [23][24], and other data. Data sources come from social media [25][26], market [27][28] and financial data [29][30], to other forms of platforms in the form of databases that can be used as analysis material.

This research problem is how to overcome these challenges to optimize the application of sentiment analysis in decision making. It allows organizations to gain valuable insights from people's views and customer responses, simplify data-driven decision-making, improve products, and devise efficient marketing strategies [31]. The stages carried out to provide analysis results are starting from analyzing the problem, obtaining and processing data, applying sentiment analysis methods to the performance of the model that will provide recommendations to predicting the results of case studies with different data in the future. Finally, sentiment evaluation greatly influences social and political conversations, providing researchers and policymakers with insight into people's views on important topics. This leads to encouraging more targeted and responsive decision making [32].

This article aims to outline the importance of sentiment analysis in the decision-making process in various sectors, such as government, business, healthcare, and media. The state of the art in this research includes the evaluation of techniques such as Deep Learning, lexicon-based, and Machine Learning using evaluation matrices such as F1-score, precision, recall, and accuracy. The novelty of this research is the assessment of 100-200 current studies in the period 2020-2024 and the identification of practical solutions to key challenges in sentiment analysis. The literature review showed that Deep Learning techniques achieved an average accuracy of 93.04%, lexicon-based approaches achieved 88.3% accuracy, and Machine Learning achieved 83.58% accuracy. The main focus is on how sentiment analysis can provide deep insights into public opinion, support more informed decision-making, and address specific challenges such as hidden dissatisfaction and rapid crisis response. This article offers a fresh perspective by integrating recent trends and advances in NLP, as well as highlighting the importance of attention to ethical issues such as data privacy and algorithmic bias, to ensure fair and effective use.

The contribution of this research is to provide deep insights into how sentiment analysis techniques can be optimized for policy-making, as well as offer practical solutions to overcome the main challenges faced in the application of sentiment analysis. Based on this, this article is expected to encourage the advancement of sentiment analysis technology as a decision-making recommendation. The many challenges and limitations faced by sentiment analysis make it increasingly complex to apply into ideal policy recommendations. Potential solutions include techniques or methods to address issues such as contextual ambiguity and punctuation, bias in data sets, use of fake accounts, and multilingualism. This leads to the outcome of analyzing the impact of the policy as it is based on data and analysis. The contribution of this research is to provide in-depth insights into how sentiment analysis techniques can be optimized for policy making as well as offer practical solutions to overcome the main challenges faced in the application of sentiment analysis.

II. Overview

Keele et al (2007) introduced the Systematic Literature Review (SLR) technique [2] and was used in this study. This method was used for several important reasons such as enabling comprehensive data collection and analysis from multiple studies and ensuring that all relevant evidence is considered in a systematic and unbiased manner. This review followed the Preferred Reporting Items for the Systematic Reviews and Meta-Analysis (PRISMA) [33]. The process includes four steps: research question setting, literature search, data screening, and data analysis as shown in Fig. 1.

The main focus of this article is to outline how sentiment analysis can provide deep insights into public opinion and support more informed decisions. The article also highlights how to address challenges such as hidden dissatisfaction, crisis response and increased engagement. In addition, the article offers a new perspective by integrating recent advances in natural language processing (NLP) and emphasizing the importance of attention to ethical issues such as data privacy and algorithmic bias. Through examples and case studies, this article will illustrate the practical application and effectiveness of sentiment analysis in supporting better policy-making and more effective business decisions.

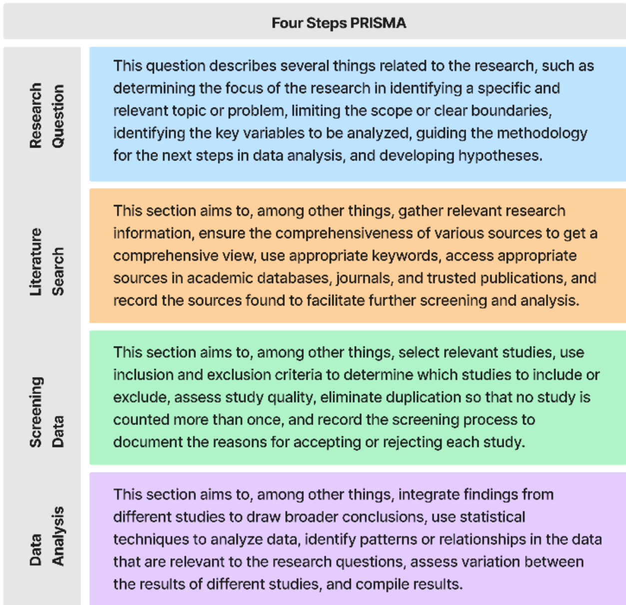

Fig. 1. Four steps PRISMA

Fig. 1 shows the PRISMA process in a systematic review consisting of four main steps. First, setting the research question helps to clearly define the focus and direction of the study. Second, a literature search is conducted to collect all relevant studies using appropriate keywords. Third, data screening ensures only quality and criterion-compliant studies are included in the analysis. Finally, data analysis integrates the findings and applies statistical methods to identify patterns and conclusions. This entire process ensures the review is conducted in a systematic and transparent manner.

A. *Research Question*

Some of these general questions will illustrate the discussion in the research conducted.

- Q1: What are the resources used for data collection in research?
- Q2: What are the sectors that utilize sentiment analysis?
- Q3: What are the best algorithms in each field that utilize sentiment analysis?
- Q4: How can sentiment analysis be used as a policy recommendation?

- Q5: What are the challenges, solutions, and opportunities of applying sentiment analysis when used as a policy recommendation?

B. *Literature Search*

Some of the research sources reviewed in this study come from search platforms such as IEEE Xplore, ScienceDirect, SpringerLink, Google Scholar and ACM Digital Library. This platform was chosen for data collection due to its high quality and reputation. IEEE Xplore excels in engineering and information technology, ScienceDirect provides peer-reviewed journals in various disciplines, ACM Digital Library is a major source of computer science and engineering research, SpringerLink offers comprehensive collections in science, technology, and medicine, and google scholar because it has free access, wide coverage, ease of use, and author monitoring. The research used as a source is research related to the topic of sentiment analysis in the 2020 to 2024-time span of 100-200 research references and the language used. These studies are taken because they have relevance to the topics discussed in this study. The research covered a wide range of sources, including journal articles, proceedings, books and reports relevant to sentiment analysis as a policy recommendation. This approach was chosen to provide a comprehensive picture and strengthen the validity of the research by considering diverse perspectives. Some keywords used as a search reference such as "machine learning, sentiment analysis in health, economy, education, e-commerce", and several other keywords. The relevance criteria of the topics searched are based on keywords with the limitation of the approach used, namely sentiment analysis in policy recommendations. The sources searched will be taken at least one reference to strengthen the explanation and justification given in the paper.

C. *Screening Data*

The collected research is reviewed regarding important points such as research objectives, methods used, frameworks to techniques used in each study. This is useful as new knowledge in the preparation of this research. In addition, these studies aim to find out the gaps that exist in them when compared to other similar studies. The literature review lasted for approximately three months by analyzing scientific research to support the analysis of this study. The inclusion criteria used included studies published in the reviewed scientific journals, studies on sentiment analysis as well as SLR scientific journal studies with complete results and case studies in various fields. While the exclusion criteria used such as studies that do not only focus on the topic of sentiment analysis that is not used as a policy and studies that do not provide complete data and results. Sentiment analysis, which is part of emotion, does not yet have a standardized standard to define and classify it academically [32].

D. *Data Analysis*

The quality assessment criteria used in this article are replication and relevance of findings. Replicability indicates that a study found is considered procedurally the same and obtains the same results and relevance indicates that a study has meaning or significance for a wider context or population. In addition to these criteria, this research is carried out assessment criteria in the form of a scale or bibliography which includes aspects such as study design, data collection methods, algorithms, data analysis, and conclusions. Study quality assessment also involves two or more independent assessors to reduce bias and get the best score for the references used in the study.

III. Fundamental Concepts of NLP in Sentiment Analysis

A. *Introduction NLP in Sentiment Analysis*

Sentiment analysis is one of the most widely used approaches in decision-making for companies, institutions, and even personalities to provide policy recommendations. This is certainly a matter that needs to be maintained by sentiment analysis so that it still has confidence in its implementation in a decision. Sentiment analysis has stages of data collection from sources such as social media, preprocessing involving text cleaning and normalization, and feature extraction to identify important elements of the text. Data labeling then classifies the text into positive, neutral, or negative sentiment, although challenges often arise from irregular text and language variations. Classification models use machine learning to predict sentiment, improving accuracy through labeled data. The importance of the relationship between NLP, artificial intelligence, and machine learning helps deal with this complexity, especially when dealing with cultural differences and non-textual symbols. Sentiment analysis is essential in understanding public opinion on a particular topic on social media [34], [35]. The relationship between Artificial Intelligence, NLP, Machine Learning and Sentiment Analysis is depicted in Fig. 2 [36].

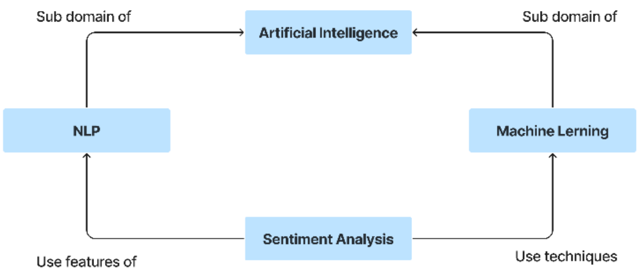

Fig. 2. Relationship between Artificial Intelligence, NLP, Machine Learning and Sentiment Analysis

One important aspect in sentiment analysis is the labeling of data that is combined into sentiment classes to reflect the sentiment expressed [37]. Sentiment classes generally consist of positive, neutral and negative which are represented as 1, -1, and 0 [38]. There are many challenges in determining the best sentiment analysis model that matches user demand, especially when labeling irregular text. Data often comes from various language styles and the use of non-textual symbols, such as emotions and vernacular, which affect the analysis results. Cultural differences can also be an obstacle. For example, terms or expressions used in one culture can have different meanings in another culture, which can lead to errors in sentiment classification. In addition, informal language styles or the use of symbols and emojis in text can add complexity to sentiment recognition. Innovative solutions are needed to overcome these obstacles, so that sentiment analysis can be more effective in understanding and accurately recognizing human sentiment.

B. Sentiment Analysis Concepts

This section provides an overview of sentiment analysis. The framework provided is the general stage adopted when conducting the sentiment analysis process as shown in Fig. 3 [39].

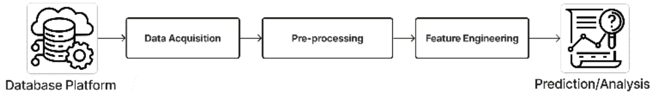

Fig. 3. General sentiment analysis framework

Fig. 3 shows common stages that are widely used in sentiment analysis. Starting from the platform database which can be in the form of social media, websites, financial data, user data, spending data and others. Furthermore, at the data acquisition stage, the data collection process is carried out using certain techniques, such as social media that uses crawling [38][40][41], websites that use scrapping [42][43], survey [44][45], and other data collection techniques. The next stage is Preprocessing which takes a crucial and essential role in NLP. Because the collected text may have unique features and numerical data that cause interference, data preprocessing is vital to reducing data size and increasing the efficiency of the system to be used [46] with the steps of data cleansing, tokenization, stopping word deletion, normalization, etc [47] as common stages performed in preprocessing. After feature engineering, the next stage is feature extraction, selection, and representation [48]. Features are obtained from previously processed information. These features reflect the meaning of the original text in the form of numbers, which correspond to the algorithm used [49]. The final stage is the sentiment and analysis process which is influenced by sentiment scores and strengths and orientations [39]. This process also includes an evaluation process as part of the analysis that measures the quality of the model created. To find out how effective a model performance is, an evaluation is carried out using data that is not used during testing and training. Model evaluation is done using evaluation metrics such as recall, precision, F1-Score [50][51] because the results of scores at high accuracy do not guarantee the validity of the model [52]. Metrics such as recall, precision, and F1-Score are used to assess the effectiveness of the model. Precision measures the accuracy of positive predictions, while recall measures the proportion of positive data that is actually detected. F1-Score is the harmonic mean of precision and recall, assessing the balance of the two. High accuracy does not necessarily reflect the validity of the model, especially if the data is not balanced. Additional metrics such as ROC-AUC, which measures the model's ability to distinguish between positive and negative classes, are also important for a thorough evaluation.

Sentiment analysis can be divided into two approaches: lexicon-based approaches, which build large collections of diverse sentiments, and machine learning approaches combined with lexicon-based approaches [53]. The approach to classifying sentiments based on machine learning can be divided into two methods, namely supervised and unsupervised learning. Supervised methods often use a large number of labeled training documents. On the other hand, when labeled training documents are hard to find, unsupervised methods are used [54] as shown in the chart in Fig. 4 [55].

Fig. 4 shows popular sentiment classification techniques and their algorithms, such as machine learning and lexicon-based approaches. Machine learning is a language feature based approach while lexicon based is based on a lexicon that has been built on top of a previously recognized sentiment lexicon [55].

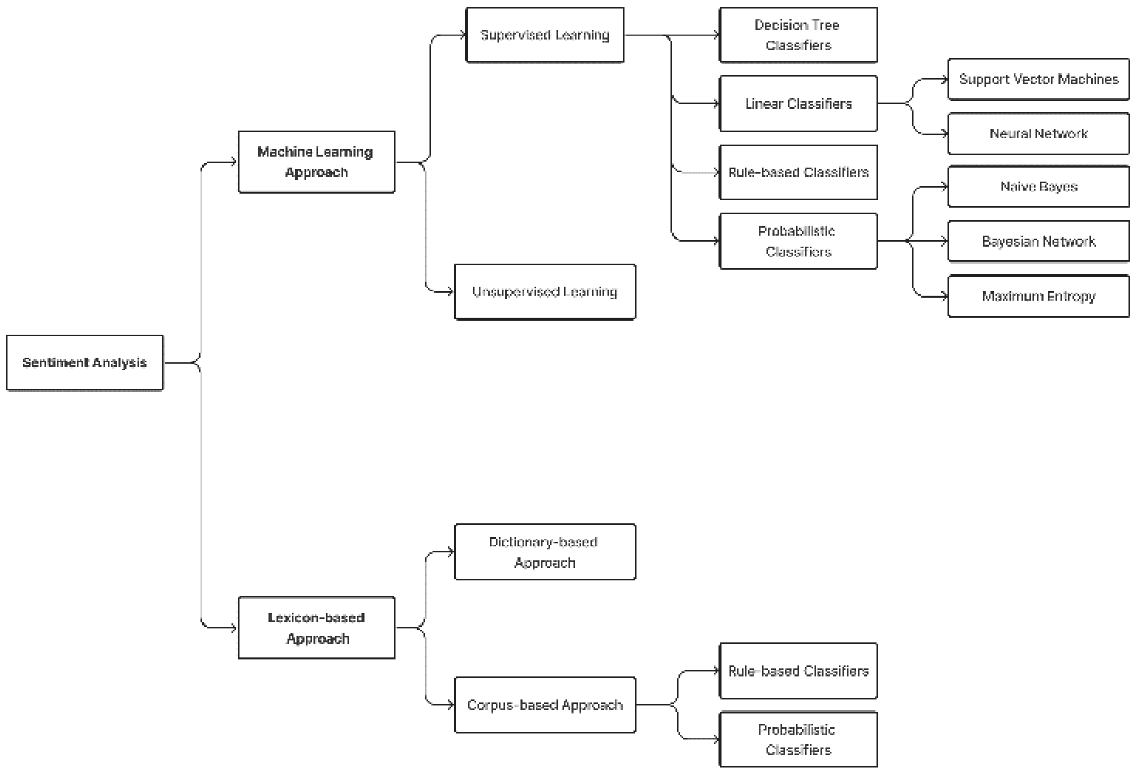

Fig. 4. Sentiment classification techniques

Machine learning approaches have advantages such as high accuracy, adaptability to the nuances of new languages or specific domains, and the ability to handle complex sentences and broader contexts. However, these approaches require a large amount of labeled data for training, the training process can be time-consuming and computationally resource-intensive, and they are prone to overfitting if not trained properly. On the other hand, the lexicon-based approach is simpler and easier to implement as it does not require labeled training data, is faster, and requires less computational resources. However, they rely on the vocabulary used, which may not cover all language variations or specialized domains, lack the ability to understand context and nuances in complex sentences such as irony or sarcasm, and are difficult to adapt to new languages or terms without lexicon updates.

1) Machine Lerning Approach: Machine learning is one of the techniques used in sentiment analysis and consists of several well-known algorithms. However, despite its advantages for handling frequently used sentiment analysis topics, machine learning has a great potential for overvitting due to its learning model with diverse features and combinations [56]. Some of these algorithms are categorized into supervised learning and unsupervised learning.

a) Supervised Learning: Each supervised machine learning workflow process trains a model with a set of input and output data. This "learning" process occurs when the model iteratively adjusts its parameters so that its predictions match the input-based outputs with a desired level of accuracy [57]. In the design process, specific objectives are often considered so that materials and machines can respond to the applied forces as desired or constrained [58]. Supervised learning generates new data based on prior knowledge [59]. Supervised learning involves the use of labeled datasets, where each input has a corresponding label. The goal of supervised learning is to learn from this data and make predictions or decisions for new, unlabeled data. Machine learning approaches consist of decision tree classifiers, linear classifiers, rule-based classifiers, and probabilistic classifiers. Among them are several algorithms that are included in supervised learning, namely Support Vector Machine (SVM), Logistic Regression (LR) [60], K-Nearest Neighbor (KNN) [61], Naïve Bayes [62], Neural Network [63], Bayesian Network [64], Minimum Entropy [65], etc. Like SVM and Naive Bayes, it can work under various conditions. SVMs find a hyperplane in the feature space that separates the classes of data by the largest margin. However, SVM may be less effective if the data is very noisy or not linearly separable, although kernels can help in some cases. Even Naive Bayes which works based on Bayes' theorem with the assumption of independence between features. However, Naïve Bayes may be less effective if there is a strong correlation between features due to the underlying independence assumption.

b) Unsupervised Learning: Unsupervised learning is an unsupervised approach to machine learning where the data submitted to the algorithm has not been categorized beforehand [66]. Unsupervised learning finds patterns and structures in unlabeled data and reveals hidden information [67]. Unsupervised learning can recognize differences among a large sample group from different points of view, reflecting the primary way humans and animals learn. Rather than getting direct instruction, we make sense of our surroundings through observation and inference, identifying basic patterns without constant feedback [68]. These algorithms have no known targets or outputs to learn from, so the goal is to identify underlying relationships, groups, or distributions of data.

2) Lexicon-based Approach: Lexicon-based methods are used to automatically label the training data [69]. Lexicon-based sentiment analysis utilizes a pre-defined lexicon to find a text whether the sentiment is positive or negative [70].

a) Dictionary-based Approach: Dictionary-based approach is manually generated by humans with direct involvement and the chances of misprediction are less but it requires a lot of effort to execute [71].

b) Corpus-based Approach: Researchers are provided with language corpora in the form of structured methods for researchers in language sampling, thus contributing to more effective research [72]. Language research using a corpus allows researchers to research how good and valid the test content is using the analytical capabilities of computational linguistics [73]. The corpus-based approach is divided into rule-based classifier and probabilistic classifier.

IV. Sentiment Analysis Application

Sentiment analysis is also referred to as bipartition-oriented emotion analysis [74]. This is explained in research [75] which focuses on the analysis of positive/negative bipartition emotions or positive/negative/neutral tripartition. Finally, sentiment analysis has different applications to different sectors in the industry by processing public opinion to emerging sentiments [2].

Sentiment analysis can influence decisions in policymaking by providing insights into public opinion in real-time. For example, governments can use sentiment analysis from social media and news platforms to understand public reaction to certain policies, such as tax changes or healthcare legislation. If negative sentiment increases, policymakers can re-evaluate their approach, make adjustments, or engage the public in dialog to address concerns raised. This enables a faster and more appropriate response to public needs and expectations, and helps ensure that policies are better received and effective.

A. E-Commerce

Sentiment analysis is useful when applied to the field of ecommerce because it makes it easier for companies to track the products and services provided to users. Sentiment analysis is applied in ecommerce to be able to provide an assessment of the level of customer satisfaction in order to evaluate the product for the better and facilitate product marketing [76]. Table I talks about some applications of sentiment analysis in e-commerce.

B. Healthcare

The use of machine learning and natural language processing technologies in the healthcare industry is now considered an important area of research, especially in measuring public sentiment [82]. Sentiment analysis is also in high demand in the healthcare field. Because it can help get feedback on policies issued in this health domain. Table II shows the application of sentiment analysis in the health sector.

TABLE I. SUMMARY OF THE APPLICATION OF SENTIMENT ANALYSIS IN E-COMMERCE

Ref.	Description
[77]	Analyze data from several merchants on the Shopee platform for customer reviews related to the quality of goods and services. It was found that the c and gamma parameter scores had a significant influence on the accuracy and F1-score of the classifier.
[78]	Explore review detectors using aspect-based sentiment analysis by considering product type. By utilizing review data from Amazon, there are two important aspects to detect this.
[79]	Predicting consumer behavior and evaluating its relationship with brain activity Sentiment analysis models demonstrate high accuracy in predicting preferences towards products.
[80]	Analyzing the utilization of recommendation systems for product evaluation and customer preferences in e-commerce Sentiment analysis and the Hybrid Recommendation Model yield better results and outperform traditional models in evaluating criteria.
[81]	Personalization chatbot with sentiment analysis features improves the performance of the question and answer system by providing tailored responses, as evidenced by a significant increase in user satisfaction in e-commerce applications.

TABLE II. SUMMARY OF THE APPLICATION OF SENTIMENT ANALYSIS IN HEALTHCARE

Ref.	Description
[83]	Analyzed Indonesian public sentiment towards the COVID-19 vaccine on Twitter from September 2020 to June 2021 with a total of 262306 tweets, using manual labeling methods and data processing including slang word removal and word embedding testing using Fasttext and GloVe.
[84]	The spread of false information about COVID-19 is a serious concern because it disrupts virus control efforts and puts lives at risk. The study aims to analyze the types of misinformation that are spread and develop an analytical approach to tackling COVID-19 fake news.
[85]	Analyze Twitter's sentiment towards nursing education during the COVID-19 pandemic. The results showed a majority of positive sentiment, highlighting the importance of supporting nurses and nursing students in crises such as the pandemic.
[86]	Highlighting the differences in sentiment analysis focus between Indonesia and other countries, as well as demonstrating the potential use of Facebook reactions as an alternative for text analysis The results show that Facebook reactions can reflect negative valence in posts, especially those related to remote learning during the COVID-19 pandemic in Indonesia.
[87]	Mobile health applications (mHealth) have become crucial in controlling the pandemic, especially with the launch of COVID-19 apps in many Arab countries Our study aims to analyze Arab users' sentiments towards COVID-19 apps and provide recommendations based on findings to enhance their effectiveness.

C. Education

In the context of education, sentiment analysis is one of the most active topics for participation in education [88]. Evaluations and responses regarding the quality of education, values in education and learning processes, and learning platforms provided to learners. Table III shows the application of sentiment analysis in the education.

TABLE III. SUMMARY OF THE APPLICATION OF SENTIMENT ANALYSIS IN EDUCATION

Ref.	Description
[89]	Analyzed a Twitter dataset about Qassim University, Saudi Arabia with 8144 tweets to explore the use of one-way analysis of variance (ANOVA) as a method for classifying opinions expressed using Arabic. SVM and Naive Bayes achieved the best results with ANOVA compared to basic experiments based on the same data.
[90]	Text data from social media plays an important role for scientists and policymakers, however, its analysis requires special attention to the challenges and limitations of using pre-defined lexicon libraries.
[91]	In the education sector, opinion mining is used to listen to students' opinions and enhance their pedagogical teaching practices With advancements in sentiment annotation techniques and artificial intelligence methodologies, student comments can be labeled with their sentiment orientation without much human intervention.
[92]	Text analytics in education has evolved into a crucial component in the architecture of future SMART campuses Sentiment analysis and qualitative feedback from students now constitute important application domains of relevant text analytics for institutions.
[93]	Online teacher training uses sentiment analysis to adapt instructional methods, despite interpretative limitations and gender bias Research findings indicate gender differences in sentiment expression, with female participants tending to send more negative messages.

D. Social Media

Sentiment analysis on social media is very effective in capturing reactions to other users' posts to explore new things [94]. Table IV shows the application of sentiment analysis in the social media.

TABLE IV. SUMMARY OF THE APPLICATION OF SENTIMENT ANALYSIS IN SOCIAL MEDIA

Ref.	Description
[95]	The diverse and ambivalent attitudes of the community towards Mobile Cabin Hospitals (MCHs) significantly impact the social sustainability of MCHs The proposed approach based on social media data (SMD) in this study aims to enhance current understanding and improve the social sustainability of MCHs.
[39]	Interest in sentiment analysis of social media and opinion mining for public security incidents has increased over time The availability of social media platforms for communication provides valuable information sources for sentiment analysis and opinion mining research.
[96]	Sentiment analysis measures user experience on social media. PLASA's hybrid model showed significant performance improvements in classifying sentiment polarity from short comments on social media, with micro-F1 scores reaching 93.94%, 90.34%, and 88.79% on the dataset used.
[97]	ChatGPT, a revolutionary chat agency launched in November 2022, is still an active topic of discussion among tech enthusiasts. The use of graph neural networks with machine learning algorithms to classify user sentiment towards ChatGPT has proven superior in terms of precision, recall, and accuracy compared to selected baselines.
[98]	The relationship is complicated between human sentiment in social media data, specifically tweet posts on platform X, the characteristics of urban buildings, and the socio-spatial dynamics of the borough of New York City (NYC). Using Natural Language Processing (NLP) techniques, particularly sentiment analysis, reinforced by the capabilities of transformer's deep learning model, RoBERTa, this study places special emphasis on the term 'Stay-at-Home' to encapsulate the apparent shift in building occupancy during the early years of the pandemic.

E. Product Review and Customer Feedback

In the business world, sentiment analysis is often used in evaluating a company's products and services [99]-[100] to feedback provided by customers. This shows the need for this sector to utilize sentiment analysis technology to recommend a policy. Table V shows the application of sentiment analysis in the product review and customer feedback.

TABLE V. SUMMARY OF THE APPLICATION OF SENTIMENT ANALYSIS IN PRODUCT REVIEW AND CUSTOMER FEEDBACK

Ref.	Description
[101]	Assessing customer satisfaction with Traveloka services through analysis of user tweets, using classification methods to analyze users' feelings about the application. The results show that the SVM method provides a better classification of Twitter users' sentiment towards the travel app's performance.
[102]	Large companies that continue to innovate and are sensitive to news in e-commerce and social media gain a competitive advantage through sentiment analysis, while this research provides guidance for researchers in determining the most effective methods for analyzing text in various languages.
[103]	The tourism and hospitality industry, especially the restaurant business, has been greatly affected by the COVID-19 pandemic Analyzing customer reviews online using the VADER model is crucial for understanding customer behavior and preferences during this unprecedented time.
[104]	The competitive airline sector has rapidly developed in the last two decades Sentiment analysis using machine learning techniques such as Naive Bayes, Support Vector Machine, and Decision Tree has been tested to analyze airline review datasets, with BERT showing better performance in criteria such as accuracy, precision, recall, and F1-score.
[105]	Grouping and identifying similarities among users of digital tourism platforms through sentiment extraction expressed in their reviews or comments, and automatically categorizing users based on the sentiment polarity in their posts Filling gaps in text mining literature for the development, enhancement, and/or adaptation of services and products in the tourism field, providing a method to explore customer needs and desires based on their digital footprint from relevant service or product posts and reviews.

F. Information Prediction

1) Election Prediction

Sentiment analysis can analyze the electability of a politician in politics [106]. This makes sentiment analysis an opportunity to become a recommendation for politicians, political parties, and other parties to be used as a suggestion in making decisions or policies. Table VI shows the application of sentiment analysis in the election prediction.

2) Other Prediction

The use of AI and NLP is not only useful, but essential for conducting effective sentiment analysis in today's data-heavy era [112]. In other sectors, sentiment analysis can be predictive to produce better quality products or services. Table VII shows the application of sentiment analysis in the other prediction.

V. LITERATURE STUDY

Many strategic policies are issued by decision-makers without regard to in-depth data and analysis. Amidst the onslaught of industries and companies that are increasingly using data, sentiment analysis comes as a practical and accurate solution in evaluating company needs in order to present effective policies for the company. This is driven by services and products that are all digitized, to make it more efficient, sentiment analysis is the solution.

TABLE VI. SUMMARY OF THE APPLICATION OF SENTIMENT ANALYSIS IN ELECTION PREDICTION

Ref.	Description
[107]	An analysis of public opinion on Twitter was conducted in the period January to March 2019 in India. It was found that candidate-1 was more popular and preferred than candidate-2 and this result was fully in line with the actual election results obtained in May 2019.
[108]	Analyze the tweets of politicians from three European countries (Greece, Spain and the United Kingdom) and explore the virality of their tweets. It found that negative tweets were more retweeted and highlighted the differences between political parties and politicians and society
[109]	Analyze more than tweets uploaded during the 2020 US presidential election and compare based on topics discussed in men and women. Significant differences between male and female users on more than 70% of topics.
[110]	Analyze differences in prediction of social media data at different levels of political democracy and on different electoral systems. The accuracy of public opinion and election predictions depends on the statistics used, adopting a standardized approach in analyzing and reporting predictions.
[111]	Analyzed more than 65,000 posts from candidate profiles on Facebook, Twitter, and Instagram with 195 presidential polls. Provides better results than traditional polls with high accuracy in predicting the final votes of candidates.

TABLE VII. SUMMARY OF THE APPLICATION OF SENTIMENT ANALYSIS IN OTHER PREDICTION

Ref.	Description
[113]	Using a transformer-based multi-task learning approach with attention mechanism, sentiment and emotion classification on crisis texts is improved, and subject intent is identified using natural language processing techniques with the publicly available general knowledge model, COMET-ATOMIC 2020, providing crucial information for crisis responders.
[79]	The development process of products faces challenges in achieving more effective and agile characteristics, while traditional methods of gathering customer data for behavior prediction are losing efficiency The significant potential of social media platforms has been discovered for customer behavior modeling, showing research results on the relationship between brain activity and consumer behavior, as well as the ability of pre-trained Python models to analyze sentiment in predicting consumer behavior and assessing its connection with brain activity during decision-making tasks.
[114]	There is significant interest in integrating sentiment analysis with graph neural networks (GNNs) for stock prediction tasks Reviewing the application of GNNs alongside sentiment analysis for stock prediction, discussing their respective contributions in the stock prediction domain, and highlighting the weaknesses of conventional methods.
[115]	Constructing a large-scale microblog dataset on government affairs and exploring the correlation between each microblog and the sentiment value of the corresponding comments below it, as well as proposing a new framework that includes data collection, sentiment analysis, and training of sentiment prediction models, which can be used as a reference for monitoring online opinions related to the government.
[116]	Predicting crude oil prices is an important yet challenging issue due to various quantitative and qualitative factors that influence them To address this complexity, it is crucial to systematically compare alternative prediction models and their variables, while considering statistical and financial performance.

In [117] revealed that proper handling of negative sentences and negation is essential to avoid sentiment bias and misclassification. The new approach proposed in this paper successfully improves the accuracy of sentiment analysis, especially when applied to Amazon reviews of cell phones. The application of negation tagging algorithms to the sentiment analysis process can provide significant benefits in understanding customer sentiment. By evaluating the effect of negation algorithms on sentiment analysis tasks, RNN achieved the best accuracy of 95.67% when combined with our negation tagging processing, exceeding its accuracy without any negative sentence identification. While the other algorithms are in order ANN + Negation 95.67%, SVM + Negation 92.54%, Naive Bayes + Negation 90.28%, SentiWordNet 64.48%, RNN 94.55%, ANN 94.08%, SVM 90.35%, and Naive Bayes 88.93%.

In [118] showed that the use of LSTM and Word2Vec models can improve sentiment understanding of hotel reviews in Indonesian with significant accuracy. Certain parameters such as the architecture and vector dimension of Word2Vec, as well as the dropout value and pooling type of LSTM play an important role in achieving the best performance. Based on the experimental research conducted through 2500 review texts as datasets, the best performance is obtained with 85.96% accuracy. The parameter combination for Word2Vec is Skip-gram architecture, Hierarchical Softmax evaluation method, and vector dimension of 300. While the parameter combination for LSTM is dropout value of 0.2, pooling type is average pooling, and learning rate is 0.001.

In [119] revealed in his research that although language models such as BERT have been used in COVID-19 sentiment analysis, there are still challenges in improving text classification directly. One additional approach is to convert single sentence classification into sentence pair classification, which has been shown to improve performance. Nonetheless, it is important to keep in mind that domain-tailored language models may be more effective than general models in understanding sentiment in a given context. The best model was found in the bert-base pair 93.20% and RoBERTa pair 93.16%.

In [120] revealed in his research that in movie sentiment analysis, the use of certain techniques such as MNB with TF-IDF vectorizer gives more accurate results compared to other techniques at 87.14%. In addition, KNN also showed equally good results with both vectorizers at 81.43%. This shows the importance of choosing the right text processing algorithms and techniques in text sentiment processing.

In [121] revealed in his research that a hybrid framework combining sentiment analysis and machine learning techniques was successfully developed to analyze customer conversations with service providers. The experimental results show that Decision Tree is the most effective technique in predicting changes in conversation polarity and the final sentiment of customer conversations with service providers at 75%. While other algorithms KNN 70%, Naive Bayes 35%, ANN, 72%, Bayes Net 74%, SVM 70%, and Logistic Regression 69%.

In [122] revealed its study to describe the dynamics of COVID-19 vaccine hesitancy over time and identify factors that influence public sentiment towards vaccination. The experiment also found that the combination of potter stemming and lemmatization can improve the model's performance in analyzing public sentiment. The best classification technique identified was the use of TextBlob sentiment score with TF-IDF vectorization and LinearSVC classification model, which resulted in high accuracy in classifying public sentiment into positive, neutral, or negative at 96.75%. Another finding is that combining two vectorization methods, CountVectorizer and TF-IDF, reduces the accuracy of the model. In conclusion, this study provides important insights into public perceptions of the COVID-19 vaccine and highlights the importance of using appropriate sentiment analysis methods in evaluating public views on vaccination.

In [123] highlighted in their research that the majority of tweets showed support for working from home, although there were also some that showed a negative attitude. The use of a Convolutional Neural Network (CNN) fine-tuned with FastText word embeddings proved more effective in analyzing the sentiment of these tweets than standard classification methods such as Support Vector Machine, Naive Bayes, Decision Tree, and Random Forest. The results of this study provide valuable insights for organizations and the general public in understanding the views and attitudes related to working from home, which can help in the development of future work policies and strategies. From the results, it is observed that on the given dataset, the proposed CNN with FastText word embedding outperforms the other classifiers with an accuracy of 92.59%.

In [124] more than 15,000 tweets have been tagged as misinformation or common vaccine tweets using reliable sources and validated by medical experts. The classification models explored are XGBoost, LSTM, and BERT transformer models. The best classification performance was obtained using BERT, yielding an F1-score of 0.98 on the test set. The precision and recall scores were 0.97 and 0.98 respectively. Machine learning-based models are effective in detecting misinformation about the COVID-19 vaccine on social media platforms.

In [125] highlighted that although there are different levels of opinion mining, opinion mining at the feature level has superior detail and complexity. Nonetheless, a key finding is that users often express their opinions in an indirect or context-based manner, signaling the need for further research to account for contextual and semantic aspects in opinion mining. Although the developed model managed to achieve high precision and recall in classifying positive and negative sentiments, the main challenge faced is in interpreting the opinions expressed indirectly by users. For the positive class, 90% precision and 87% recall were achieved, while for the negative class, 87% precision and 89.7% recall and 88.3% accuracy were achieved.

Table VIII shows the comparison between the models of commonly used algorithms in sentiment analysis. The average score for the Deep Learning model is 93.04%, Machine Learning 83.58% and Lexicon Based 88.3%. This shows that the Deep Learning model can be a recommendation for algorithms used in policy proposal recommendations.

TABLE VIII. A COMPREHENSIVE ASSESSMENT OF SENTIMENT ANALYSIS ALGORITHMS

Model	Algorithm	Average Score	Overall Average Score
Deep Learning	LSTM CNN BERT RNN ANN	85.96% 92.59% 98% 94.55% 94.08%	93.04%
Machine Learning	SVM Naïve Bayes KNN Decision Tree LinearSVC Logistic Regression	90.35% 88.93% 81.43% 75% 96.75% 69%	83.58
Lexicon-Based	Lexicon-Based	88.3%	88.3%

The choice of algorithm depends on the type of problem and data at hand. LSTM (Long Short-Term Memory) excels at processing sequential data and overcoming the problem of long-term dependencies, ideal for tasks such as text prediction and sentiment analysis, but requires large computational resources. CNN (Convolutional Neural Network) is optimized for visual data processing, such as image recognition and object detection, due to its ability to capture spatial features. BERT (Bidirectional Encoder Representations from Transformers) is leading the way in natural language understanding thanks to its ability to process bidirectional context, suitable for complex NLP tasks. RNN (Recurrent Neural Network) is similar to LSTM but less efficient at handling long dependencies, making it more suitable for short sequential data. ANN (Artificial Neural Network) is commonly used in various applications but may be less efficient than more specific models. SVM (Support Vector Machine) is effective in classification with large margins but less efficient on very large data or when features are not linearly separable. Naïve Bayes works well for text classification assuming strong independence between features, but performance degrades when this assumption is not met. KNN (K-Nearest Neighbors) is easy to implement and effective for small datasets but slow on large datasets. Decision Tree is intuitive and easy to interpret but prone to overfitting. LinearSVC is a faster variant of SVM for large linear data, while Logistic Regression is effective for simple binary classification but less suitable for highly complex data. Lexicon-Based approaches are simple and fast for sentiment analysis but less accurate than more advanced machine learning methods such as SVM and Naive Bayes.

VI. DISCUSSION

Sentiment analysis as a policy-making recommendation must certainly have confidence in today's data-heavy industry. However, in the midst of the existence of sentiment analysis, it also has several limitations and challenges that need to be resolved by researchers and professionals so that it can be trusted as a series of processes in decision making.

A. Main Findings

The main findings in this study reveal that the model can be trained to detect suspicious behavior patterns by using features such as posting frequency, language patterns, and social interactions. Machine learning techniques such as anomaly detection, clustering, and network analysis can be used. In sentiment analysis, TF-IDF can be customized with additional features from user profiles to improve detection and customization against content that may be generated by non-authentic entities.

Recent trends in NLP such as the use of large language models like BERT, GPT, and Transformer have revolutionized various NLP tasks, including sentiment analysis. The implications and explanations of the findings from this analysis suggest that transformers such as BERT have an advantage in accuracy due to their ability to understand context and recognize complex relationships in natural language. In general, deep learning models outperform traditional methods, reflecting the direction of technological development in sentiment analysis. In contrast, lexicon-based approaches remain relevant for applications that demand speed and simplicity, although they lack in context understanding. In terms of power, the use of cutting-edge techniques enables significant improvements in accuracy and context understanding capabilities.

However, there are limitations to be aware of, such as the high dependency on extensive labeled data and the need for large computational resources. Thus, combining sentiment analysis with the latest trends and methods in NLP not only improves accuracy but also provides a more comprehensive understanding of the linguistic and cultural context in text data. This has implications for improving policy decisions that can support data-driven decisions in various fields. In addition, it will boost the effectiveness of large language models in understanding language nuances, improve policy responsiveness and will encourage anticipation of challenges such as multilingualism, concept understanding, punctuation adjustment, and fake/bot accounts.

In this study, it was found that Deep Learning models such as BERT and LSTM showed higher accuracy compared to traditional lexicon-based and Machine Learning approaches. Other studies also confirmed the superiority of these techniques, showing comparable accuracy in complex sentiment analysis tasks. Meanwhile, lexicon-based approaches are often faster and easier to implement, but tend to be less effective in handling complex language nuances and contexts. Previous research has also shown that traditional models, such as Naive Bayes and SVM, require large amounts of labeled data and often struggle to capture deep context, especially in multilingual scenarios. This confirms that the adoption of large language models can be more effective in cross-language sentiment analysis applications without requiring extensive additional training. This finding strengthens the argument that the use of sophisticated models can improve the predictive ability and relevance of sentiment analysis results.

Although the results show high accuracy for various sentiment analysis models, there are some limitations that need to be noted. Small sample sizes can affect the generalizability of the findings, and the quality of the data used is critical as unclean data can degrade the accuracy of the model. In addition, models trained on certain datasets may not perform well on other datasets with different characteristics, challenging the generalizability of the findings. The robustness of the model to different types of text is also an important factor, as a model that is good at handling formal text may not perform well with informal text such as social media.

B. *Challenges, Solutions, and Opportunity of Sentiment Analysis as a Policy Recommendation*

1) *Multilingual*

One of the most important factors of the success of a sentiment analysis to be used as a tool in policy making is that it can anticipate different languages in the same case. This is a very important challenge in giving industry players confidence in utilizing sentiment analysis as a recommendation for evaluating company services or products. The possible invalidity of the results from sentiment analysis is questioned as it has not been able to handle different languages in the same case. Multilingualism is a growing field in natural language processing, where researchers seek to address the challenges associated with externalizing the language of the text [126]. This causes the results of sentiment analysis to be unjustified as they are not able to handle such cases. One of the reasons for this opinion is that sometimes many social media users in a country use mixed language or mother tongue when commenting on social media [127].

To overcome these challenges, sentiment analysis is currently developed because it has the risk of handling only one language, so techniques to handle multiple languages are proposed [128]. One of the techniques used to solve these problems is the utilization of TF-IDF to evaluate specific terms in the text. This technique has been tested in many studies in handling multiple languages and proven to be optimal in the results obtained [129]. Multilingual handling in sentiment analysis has a number of significant benefits such as market share reach that can be global due to the ability to handle multiple languages. This is possible due to the ability of sentiment analysis to handle social media users based on cultural backgrounds, countries, and regional territories that have a variety of different languages. This benefit leads to the optimization of policy making by the industry in various geographical conditions that have different language possibilities in each region.

Adapting TF-IDF in a multilingual context, it is important to separate the preprocessing of each language with appropriate tokenizers, stemming, and stop words. After preprocessing, TF-IDF can be applied to each language subset separately, or use multilingual models that can handle texts from multiple languages simultaneously, such as multilingual BERT or XLM-RoBERTa. This enables consistent analysis even if the data comes from multiple languages.

2) *Concept Understanding*

Sentiment analysis means to assess the text expressed by users towards a service or product. However, when the expressions given by users are expressions that are figurative or stylistic in conveying messages, it will be difficult to define the intent expressed if in sentiment calculation. This results in the inaccuracy of sentiment analysis in predicting the sentiment contained in the text. Sentiment analysis has the challenge of detecting the sentiment contained in the text implicitly, in contrast to text that has been explicitly exposed so that sentiment analysis is easy to determine the class [130]. The text is usually in the form of figurative language such as figure of speech, disambiguates and ambiguity. For example, in the context of "This beach is not recommended for picnics, but snorkeling" which contains negative sentiments or sentences. However, if you use the concept of sarcasm, it contains a positive sentiment meaning that visitors to the beach can utilize the tourist location for snorkeling instead of picnicking. The understanding of this concept needs to be straightened out in the interpretation of sentiment analysis in order to be able to interpret the meaning of the content of the user's message if using this style of language or figurative language.

The challenge often referred to as Word Sense Disambiguation (WSD) is the biggest challenge experienced by sentiment analysis. However, this challenge can be solved with trained language models to characterize words and data sets such as the BERT model used in one study [131]. These threats and challenges can be addressed by creating a model that can specifically determine the disambiguate contained in the entire text. Other research for example uses a semi-supervised approach to deal with disambiguate in neural senses to determine ambiguity, its levels, and accurate aspect-based sentiment prediction comparisons [132]. This provides tremendous benefits to sentiment analysis with reference to the validity of the specified class. With such solutions, sentiment analysis can understand the right context, avoid misinterpretation, improve model quality, and user experience because it provides accurate and consistent results just like humans. Finally, policy-making processes that utilize sentiment analysis approaches gain more trust in the eyes of policy makers.

Techniques such as word embeddings (Word2Vec, GloVe) or contextual embeddings (BERT, GPT) are used to capture the meaning of words in context. TF-IDF can be enhanced with these integrations to take semantics into account. Additionally, domain-specific ontologies or lexicons can be used to ensure that the model understands deeper and contextual concepts, not just word frequency.

3) *Punctuation Adjusment*

Sentiment analysis has another equally important challenge in determining the sentiment class as the outcome offered in policy making. Sometimes in comments or posts in text form, many emoticon-like models are used. This will certainly change the interpretation of sentiment analysis in determining the class because often these symbols indicate something that does not match the meaning conveyed by the text [133]. Finally, the class determined is inaccurate because it is unable to read the meaning of the message conveyed by the text with the combination of symbols.

This is one of the major challenges facing sentiment analysis. As with figurative language, sentiment analysis is trained to adapt to the conditions of using these symbols or emoticons. A model can be created to make adjustments to the condition of symbols that do not match the content of the message in the text. One of the studies [134] used LIME in decision making in modeling to handle this case. Because recognizing emoticons or emojis in sentiment analysis will provide new insights for companies in making policies based on public input. This has an impact on the solutions offered by the company and makes the right policy. The benefits of the model can make sentiment analysis more accurate because emojis are able to convey nuances of emotion that are difficult to express with text alone. In addition, it can also expand the scope of language in sentiment analysis, because emojis have universal meanings that can be understood by various cultures and languages.

Punctuation adjustment in TF-IDF and other techniques involves careful preprocessing to identify and retain important punctuation that may affect sentiment or meaning. The tokenization algorithm should be adapted to retain relevant punctuation while removing unnecessary ones. Techniques such as n-grams can also be used to capture patterns involving punctuation in text.

4) *Fake/Bot Account and Paid User Customization*

One of the challenges for sentiment analysis in enhancing trust in industry owners and companies that utilize it in generating conclusions from data management for policy making is the existence of bot accounts or fake accounts. While there are social bots for chatting, providing information, or making jokes, most studies have found that malicious fake accounts are more dominant, creating a lot of interaction and changing the dynamics of social media [135]. Sometimes to increase the rating of a service or product these accounts are used to gain the trust of other users to use the company's services or products. However, this can damage the data which makes it unqualified and damages the credibility of the opinion maker [136]. Because the data obtained still contains responses from bot accounts or computers that are deliberately created to lead other users' opinions. The same thing often happens when utilizing sentiment analysis in policymaking on the topic of politics or elections. Often many candidate success teams and even volunteers are deliberately paid to create accounts that appear to be real users and have the same goal, namely to lead public opinion and gain public trust in the proposed candidate. This will also damage the quality of data that will be used for policy making. Because the data used must be original data and not manipulated in such a way as to lead opinions. Research on the use of social bots in various situations remains relevant, especially with regard to election contests such as the 2016 US Elections, the UK's Brexit referendum on European Union membership, the 2018 Italian General Elections, and the 2017 Catalonia referendum [137].

This is just one of the many challenges sentiment analyses has in gaining the trust of its users. This can be overcome by detecting fake accounts. The fake accounts are subjected to filtering, rules or machine learning [136] until they can be classified and different from other data. As is the case in several studies [138], [139] which put forward a comparative analysis of filtering bot accounts and accounts that are not bots or often called humans. As well as the routine use of paid accounts or bots on political topics (on Twitter, for example), coupled with sentiment and the fragmentation of social media results in political polarization. However, this can be resolved with social bot detection [140]. Handling bot/fake accounts to paid accounts in sentiment analysis makes the data used more accurate and objective which leads to better and responsive policy decision-making.

In addition, some of these challenges are important to ensure that data is collected in accordance with privacy laws and checked for bias to avoid discriminatory results. This technology can be misused, so ethical guidelines must be upheld. Transparency in methods and accountability of organizations using sentiment analysis are also required, as well as clear consent from users. These are important to ensure responsible and ethical use of sentiment analysis technology.

VII. CONCLUSION

Sentiment analysis processes text to express emotions, opinions, and moods that are categorized into positive, neutral, and negative sentiments. Sentiment analysis is an important tool for companies and organizations in recommending policies. This systematic review provides new insights and an overview of the future of sentiment analysis. Many applications have applied sentiment analysis in policy making in areas such as economics, healthcare, education, e-commerce, and politics. Examples in healthcare include gauging public reaction to the Covid-19 vaccine and its impact on work patterns. Sentiment analysis techniques include Machine Learning which is efficient but requires a lot of labeled data, Deep Learning which is accurate but requires large computing resources, and Lexicon-Based which is fast but less effective in handling context.

The main results of this study show that Deep Learning techniques achieved an average accuracy of 93.04%, lexicon-based approaches achieved 88.3%, and Machine Learning achieved 83.58%. The findings highlight the importance of addressing challenges such as multilingualism, concept understanding, punctuation adjustment, fake accounts, as well as ethical issues such as data privacy and algorithmic bias. Suggested solutions include the use of large language models (LLMs) such as GPT-4 and BERT, word embedding, tokenization, and behavioral pattern analysis.

The contribution of this research is to offer practical solutions to key challenges in sentiment analysis and encourage further research with the latest technology to strengthen the relationship between policymakers and the public. Limitations of this research include reliance on available datasets and challenges in handling complex context. Future research prospects will focus on utilizing LLMs that can better understand language context and nuances, as well as the integration of multilingual models for cross-language analysis without extensive additional training.

This requires collaboration between researchers such as linguists in understanding the context of what is being discussed, policy makers as contributors to data acquisition, and IT experts in creating algorithms that are appropriate in certain cases. The future of this integration promises more inclusive and data-driven policies, strengthening the relationship between policymakers and the public. This article contributes to new knowledge in the sentiment analysis domain by identifying practical solutions and current technologies to address existing challenges, as well as encouraging similar research for updates in the field.

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REFERENCES

[1] M. M. Dakwah, A. A. Firdaus, Furizal, and R. A. Faresta, "Sentiment Analysis on Marketplace in Indonesia using Support Vector Machine and Naïve Bayes Method," *J. Ilm. Tek. Elektro Komput. dan Inform.*, vol. 10, no. 1, pp. 39–53, 2023, doi: 10.26555/jiteki.v10i1.28070.

[2] J. R. Jim, M. A. R. Talukder, P. Malakar, M. M. Kabir, K. Nur, and M. F. Mridha, "Recent advancements and challenges of NLP-based sentiment analysis: A state-of-the-art review," *Nat. Lang. Process. J.*, vol. 6, p. 100059, 2024, doi: 10.1016/j.nlp.2024.100059.

[3] L. Geni, E. Yulianti, and D. I. Sensuse, "Sentiment Analysis of Tweets Before the 2024 Elections in Indonesia Using IndoBERT Language Models," *J. Ilm. Tek. Elektro Komput. dan Inform.*, vol. 9, no. 3, pp. 746–757, 2023, doi: 10.26555/jiteki.v9i3.26490.

[4] Y. Pan, L. Hou, and X. Pan, "Interplay between stock trading volume, policy, and investor sentiment: A multifractal approach," *Phys. A Stat. Mech. its Appl.*, vol. 603, p. 127706, Oct. 2022.

[5] F. Sufi and M. Alsulami, "Identifying drivers of COVID-19 vaccine sentiments for effective vaccination policy," *Heliyon*, vol. 9, no. 9, p. e19195, Sep. 2023, doi: 10.1016/j.heliyon.2023.e19195.

[6] J. Chi, "Explaining US travel behavior with perceived threat of pandemic, consumer sentiment, and economic policy uncertainty," *Transp. Policy*, vol. 137, pp. 90–99, 2023.

[7] S. Consoli, L. Barbaglia, and S. Manzan, "Fine-grained, aspect-based sentiment analysis on economic and financial lexicon," *Knowledge-Based Syst.*, vol. 247, p. 108781, Jul. 2022.

[8] B. M. D. Abighail, Fachrifansyah, M. R. Firmanda, M. S. Anggreainy, Harvianto, and Gintoro, "Sentiment Analysis E-commerce Review," *Procedia Comput. Sci.*, vol. 227, pp. 1039–1045, 2023, doi: 10.1016/j.procs.2023.10.613.

[9] U. Rhohmawati, I. Slamet, and H. Pratiwi, "Sentiment Analysis Using Maximum Entropy on Application Reviews (Study Case: Shopee on Google Play)," *J. Ilm. Tek. Elektro Komput. dan Inform.*, vol. 5, no. 1, pp. 44–49, 2019, doi: 10.26555/jiteki.v5i1.13087.

[10] G. Fatouros, J. Soldatos, K. Kouroumali, G. Makridis, and D. Kyriazis, "Transforming sentiment analysis in the financial domain with ChatGPT," *Mach. Learn. with Appl.*, vol. 14, p. 100508, 2023, doi: 10.1016/j.mlwa.2023.100508.

[11] J. Yang, "Financial stabilization policy, market sentiment, and stock market returns," *Financ. Res. Lett.*, vol. 52, p. 103379, Mar. 2023, doi: 10.1016/j.frl.2022.103379.

[12] S. Liu and J. Liu, "Public attitudes toward COVID-19 vaccines on English-language Twitter: A sentiment analysis," *Vaccine*, vol. 39, no. 39, pp. 5499–5505, 2021, doi: 10.1016/j.vaccine.2021.08.058.

[13] J. Serrano-Guerrero, M. Bani-Doumi, F. P. Romero, and J. A. Olivas, "A 2-tuple fuzzy linguistic model for recommending health care services grounded on aspect-based sentiment analysis," *Expert Syst. Appl.*, vol. 238, 2024, doi: 10.1016/j.eswa.2023.122340.

[14] K. Fuller, C. Lupton-Smith, R. Hubal, and J. E. McLaughlin, "Automated Analysis of Preceptor Comments: A Pilot Study Using Sentiment Analysis to Identify Potential Student Issues in Experiential Education," *Am. J. Pharm. Educ.*, vol. 87, no. 9, p. 100005, Sep. 2023, doi: 10.1016/j.ajpe.2023.02.005.

[15] M. Gonzalez-Igual, T. Corzo Santamaria, and A. Rua Vieites, "Impact of education, age and gender on investor's sentiment: A survey of practitioners," *Heliyon*, vol. 7, no. 3, p. e06495, Mar. 2021, doi: 10.1016/j.heliyon.2021.e06495.

[16] S. Huang and M. Zeng, "Political sentiment and MAX effect," *The North American Journal of Economics and Finance*, vol. 62, p. 101760, 2022.

[17] D. O. Oyewola, L. A. Oladimeji, S. O. Julius, L. B. Kachalla, and E. G. Dada, "Optimizing sentiment analysis of Nigerian 2023 presidential election using two-stage residual long short term memory," *Heliyon*, vol. 9, no. 4, 2023, doi: 10.1016/j.heliyon.2023.e14836.

[18] A. A. Firdaus, A. Yudhana, I. Riadi, and Mahsun, "Indonesian presidential election sentiment: Dataset of response public before 2024," *Data Br.*, vol. 52, p. 109993, 2024, doi: 10.1016/j.dib.2023.109993.

[19] X. Xing, H. Huang, and C. P. T. Hedenstierna, "Selling through online marketplaces with consumer profiling," *J. Bus. Res.*, vol. 164, p. 114022, Sep. 2023, doi: 10.1016/j.jbusres.2023.114022.

[20] N. K. Nissa and E. Yulianti, "Multi-label text classification of Indonesian customer reviews using bidirectional encoder representations from transformers language model," *Int. J. Electr. Comput. Eng.*, vol. 13, no. 5, pp. 5641–5652, 2023, doi: 10.11591/ijece.v13i5.pp5641-5652.

[21] K. S. Mohammed, H. Obeid, K. Oueslati, and O. Kaabia, "Investor sentiments, economic policy uncertainty, US interest rates, and financial assets: Examining their interdependence over time," *Financ. Res. Lett.*, vol. 57, p. 104180, Nov. 2023, doi: 10.1016/j.frl.2023.104180.

[22] J. Xiao, J. Jiang, and Y. Zhang, "Policy uncertainty, investor sentiment, and good and bad volatilities in the stock market: Evidence from China," *Pacific-Basin Financ. J.*, vol. 84, p. 102303, Apr. 2024, doi: 10.1016/j.pacfin.2024.102303.

[23] H. O. Ahmad and S. U. Umar, "Sentiment Analysis of Financial Textual data Using Machine Learning and Deep Learning Models," *Inform.*, vol. 47, no. 5, pp. 153–158, 2023, doi: 10.31449/inf.v47i5.4673.

[24] A. Abayomi-Alli, O. Abayomi-Alli, S. Misra, and L. Fernandez-Sanz, "Study of the Yahoo-Yahoo Hash-Tag Tweets Using Sentiment Analysis and Opinion Mining Algorithms," *Inf.*, vol. 13, p. 152, 2022, doi: 10.3390/info13030152.

[25] R. A. Arilya, Y. Azhar, and D. R. Chandranegara, "Sentiment Analysis on Work from Home Policy Using Naïve Bayes Method and Particle Swarm Optimization," *J. Ilm. Tek. Elektro Komput. dan Inform.*, vol. 7, no. 3, pp. 433–440, 2021, doi: 10.26555/jiteki.v7i3.22080.

[26] D. Jeong, S. Hwang, J. Kim, H. Yu, and E. Park, "Public perspective on renewable and other energy resources: Evidence from social media big data and sentiment analysis," *Energy Strateg. Rev.*, vol. 50, p. 101243, Nov. 2023, doi: 10.1016/j.esr.2023.101243.

[27] J. Li and H.-J. Ahn, "Sensitivity of Chinese stock markets to individual investor sentiment: An analysis of Sina Weibo mood related to COVID-19," *J. Behav. Exp. Financ.*, vol. 41, p. 100860, Mar. 2024, doi: 10.1016/j.jbef.2023.100860.

[28] Z. Hu and P.-W. Sun, "Salience theory, investor sentiment, and commonality in sentiment: Evidence from the Chinese stock market," *J. Behav. Exp. Financ.*, p. 100934, Apr. 2024, doi: 10.1016/j.jbef.2024.100934.

[29] M. Lengkeek, F. van der Knaap, and F. Frasincar, "Leveraging hierarchical language models for aspect-based sentiment analysis on financial data," *Inf. Process. Manag.*, vol. 60, no. 5, 2023, doi: 10.1016/j.ipm.2023.103435.

[30] K. Kirtac and G. Germano, "Sentiment trading with large language models," *Financ. Res. Lett.*, vol. 62, p. 105227, Apr. 2024, doi: 10.1016/j.frl.2024.105227.

[31] A. A. A. Ahmed, S. Agarwal, Im. G. A. Kurniawan, S. P. D. Anantadjaya, and C. Krishnan, "Business boosting through sentiment analysis using Artificial Intelligence approach," *Int. J. Syst. Assur. Eng. Manag.*, vol. 13, pp. 699–709, Mar. 2022, doi: 10.1007/s13198-021-01594-x.

[32] S. Peng *et al.*, "A survey on deep learning for textual emotion analysis in social networks," *Digit. Commun. Networks*, vol. 8, no. 5, pp. 745–762, 2022, doi: 10.1016/j.dcan.2021.10.003.

[33] R. Sarkis-Onofre, F. Catalá-López, E. Aromataris, and C. Lockwood, "How to properly use the PRISMA Statement," *Syst. Rev.*, vol. 10, no. 1, p. 117, Dec. 2021, doi: 10.1186/s13643-021-01671-z.

[34] R. K. Behera, M. Jena, S. K. Rath, and S. Misra, "Co-LSTM: Convolutional LSTM model for sentiment analysis in social big data," *Inf. Process. Manag.*, vol. 58, no. 1, p. 102435, Jan. 2021, doi: 10.1016/j.ipm.2020.102435.

[35] N. H. B. Suhendra, P. Keikhosrokiani, M. P. Asl, and X. Zhao, "Opinion mining and text analytics of literary reader responses: A case study of reader responses to KL Noir volumes in Goodreads using sentiment analysis and topic," *Handbook of research on opinion mining and text analytics on literary works and social media*, pp. 191–239, 2022, doi: 10.4018/978-1-7998-9594-7.ch009.

[36] S. Hosgurmath, V. Petli, and V. K. Jalihal, "An omicron variant tweeter sentiment analysis using NLP technique," *Glob. Transitions Proc.*, vol. 3, no. 1, pp. 215–219, 2022, doi: 10.1016/j.gltp.2022.03.025.

[37] A. H. Pratama and M. Hayaty, "Performance of Lexical Resource and Manual Labeling on Long Short-Term Memory Model for Text Classification," *J. Ilm. Tek. Elektro Komput. dan Inform.*, vol. 9, no. 1, pp. 74–84, 2023, doi: 10.26555/jiteki.v9i1.25375.

[38] A. Zahri, R. Adam, and E. B. Setiawan, "Social Media Sentiment Analysis using Convolutional Neural Network (CNN) dan Gated Recurrent Unit (GRU)," *J. Ilm. Tek. Elektro Komput. dan Inform.*, vol. 9, no. 1, pp. 119–131, 2023, doi: 10.26555/jiteki.v9i1.25813.

[39] M. S. Md Suhaimin, M. H. Ahmad Hijazi, E. G. Moung, P. N. E. Nohuddin, S. Chua, and F. Coenen, "Social media sentiment analysis and opinion mining in public security: Taxonomy, trend analysis, issues and future directions," *J. King Saud Univ. - Comput. Inf. Sci.*, vol. 35, no. 9, 2023, doi: 10.1016/j.jksuci.2023.101776.

[40] N. M. Azahra and E. B. Setiawan, "Sentence-Level Granularity Oriented Sentiment Analysis of Social Media Using Long Short-Term Memory (LSTM) and IndoBERTweet Method," *J. Ilm. Tek. Elektro Komput. dan Inform.*, vol. 9, no. 1, pp. 85–95, 2023, doi: 10.26555/jiteki.v9i1.25765.

[41] Pristiyono, M. Ritonga, M. A. Al Ihsan, A. Anjar, and F. H. Rambe, "Sentiment analysis of COVID-19 vaccine in Indonesia using Naïve Bayes Algorithm," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 1088, no. 1, p. 012045, 2021, doi: 10.1088/1757-899x/1088/1/012045.

[42] A. Shukla, C. Bansal, S. Badhe, M. Ranjan, and R. Chandra, "An evaluation of Google Translate for Sanskrit to English translation via sentiment and semantic analysis," *Nat. Lang. Process. J.*, vol. 4, p. 100025, 2023, doi: 10.1016/j.nlp.2023.100025.

[43] M. Chiny, M. Chihab, Y. Chihab, and O. Bencharef, "LSTM, VADER and TF-IDF based Hybrid Sentiment Analysis Model," *Int. J. Adv. Comput. Sci. Appl.*, vol. 12, no. 7, pp. 265–275, 2021, doi: 10.14569/IJACSA.2021.0120730.

[44] E. A. Metheney and E. Lust, "Zambian election panel survey: Dataset of responses before, near, and after 2021 elections," *Data Br.*, vol. 48, 2023, doi: 10.1016/j.dib.2023.109073.

[45] G. Nguyen *et al.*, "Machine Learning and Deep Learning frameworks and libraries for large-scale data mining: a survey," *Artif. Intell. Rev.*, vol. 52, no. 1, pp. 77–124, 2019, doi: 10.1007/s10462-018-09679-z.

[46] D. Suleiman, A. Odeh, and R. Al-Sayyed, "Arabic Sentiment Analysis Using Naïve Bayes and CNN-LSTM," *Inform.*, vol. 46, no. 6, pp. 79–86, 2022, doi: 10.31449/inf.v46i6.4199.

[47] M. Subramanian, V. Easwaramoorthy Sathiskumar, G. Deepalakshmi, J. Cho, and G. Manikandan, "A survey on hate speech detection and sentiment analysis using machine learning and deep learning models," *Alexandria Eng. J.*, vol. 80, pp. 110–121, 2023, doi: 10.1016/j.aej.2023.08.038.

[48] C. I. Eke, A. A. Norman, Liyana Shuib, and H. F. Nweke, "Sarcasm identification in textual data: systematic review, research challenges and open directions," *Artif. Intell. Rev.*, vol. 53, no. 6, pp. 4215–4258, Aug. 2020, doi: 10.1007/s10462-019-09791-8.

[49] A. Kulkarni and A. Shivananda, *Natural Language Processing Recipes*. Berkeley, CA: Apress, 2019, doi: 10.1007/978-1-4842-4267-4.

[50] N. Sultan, "Sentiment Analysis of Amazon Product Reviews using Supervised Machine Learning Techniques," *Knowl. Eng. Data*, vol. 5, no. 1, pp. 101–108, 2022, doi: 10.1007/978-3-030-63319-6_68.

[51] K. Trang and A. H. Nguyen, "A Comparative Study of Machine Learning-based Approach for Network Traffic Classification," *Knowl. Eng. Data Sci.*, vol. 4, no. 2, p. 128, 2022, doi: 10.17977/um018v4i22021p128-137.

[52] H. Syahputra and A. Wibowo, "Comparison of Support Vector Machine (SVM) and Random Forest Algorithm for Detection of Negative Content on Websites," *J. Ilm. Tek. Elektro Komput. dan Inform.*, vol. 9, no. 1, pp. 165–173, 2023, doi: 10.26555/jiteki.v9i1.25861.

[53] Z. Fu, Y. C. Hsu, C. S. Chan, C. M. Lau, J. Liu, and P. S. F. Yip, "Efficacy of ChatGPT in Cantonese Sentiment Analysis: Comparative Study," *J. Med. Internet Res.*, vol. 26, p. e51069, 2024, doi: 10.2196/51069.

[54] R. Sisodiya and P. K. Mannepalli, "A Survey on Social Digital Data-Based Sentiment Mining Techniques and Feature," *Int. J. Comput. Trends Technol.*, vol. 69, no. 4, pp. 34–38, Apr. 2021, doi: 10.14445/22312803/IJCTT-V69I4P107.

[55] J. Abate and F. Rashid, "A review of sentiment analysis for Afaan Oromo: Current trends and future perspectives," *Nat. Lang. Process. J.*, vol. 6, p. 100051, 2024, doi: 10.1016/j.nlp.2023.100051.

[56] M. S. Islam *et al.*, "Machine Learning-Based Music Genre Classification with Pre-Processed Feature Analysis," *J. Ilm. Tek. Elektro Komput. dan Inform.*, vol. 7, no. 3, p. 491, 2022, doi: 10.26555/jiteki.v7i3.22327.

[57] P. K. Lim, I. Julca, and M. Mutwil, "Redesigning plant specialized metabolism with supervised machine learning using publicly available reactome data," *Comput. Struct. Biotechnol. J.*, vol. 21, pp. 1639–1650, 2023, doi: 10.1016/j.csbj.2023.01.013.

[58] M. Stern, D. Hexner, J. W. Rocks, and A. J. Liu, "Supervised Learning in Physical Networks: From Machine Learning to Learning Machines," *Phys. Rev. X*, vol. 11, no. 2, pp. 1–18, 2021, doi: 10.1103/PhysRevX.11.021045.

[59] H. Hassan *et al.*, "Supervised and weakly supervised deep learning models for COVID-19 CT diagnosis: A systematic review," *Comput. Methods Programs Biomed.*, vol. 218, 2022, doi: 10.1016/j.cmpb.2022.106731.

[60] Koirunnisa, A. M. Siregar, and S. Faisal, "Optimized Machine Learning Performance with Feature Selection for Breast Cancer Disease Classification," *J. Ilm. Tek. Elektro Komput. dan Inform.*, vol. 9, no. 4, pp. 1131–1143, 2023, doi: 10.26555/jiteki.v9i4.27527.

[61] R. A. Asmara, N. D. Hendrawan, A. N. Handayani, and K. Arai, "Basketball Activity Recognition Using Supervised Machine Learning Implemented on Tizen OS Smartwatch," *J. Ilm. Tek. Elektro Komput. dan Inform.*, vol. 8, no. 3, p. 447, 2022, doi: 10.26555/jiteki.v8i3.23668.

[62] D. Petschke and T. E. M. Staab, "A supervised machine learning approach using naive Gaussian Bayes classification for shape-sensitive detector pulse discrimination in positron annihilation lifetime spectroscopy (PALS)," *Nucl. Instruments Methods Phys. Res. Sect. A Accel. Spectrometers, Detect. Assoc. Equip.*, vol. 947, p. 162742, Dec. 2019, doi: 10.1016/j.nima.2019.162742.

[63] Y. Zhao and J. Han, "Offline supervised learning v.s. online direct policy optimization: A comparative study and a unified training paradigm for neural network-based optimal feedback control," *Phys. D Nonlinear Phenom.*, vol. 462, p. 134130, Jun. 2024, doi: 10.1016/j.physd.2024.134130.

[64] L. Chen, X. Jiang, and Y. Wang, "A Bayesian network learning method for sparse and unbalanced data with GNN-based multilabel classification application," *Appl. Soft Comput.*, vol. 154, 2024, doi: 10.1016/j.asoc.2024.111393.

[65] S. Li, F. Liu, Z. Hao, L. Jiao, X. Liu, and Y. Guo, "MinEnt: Minimum entropy for self-supervised representation learning," *Pattern Recognit.*, vol. 138, p. 109364, Jun. 2023, doi: 10.1016/j.patcog.2023.109364.

[66] J. L. Thenier-Villa, F. R. Martínez-Ricarte, M. Figueroa-Vezirian, and F. Arikan-Abelló, "Glioblastoma Pseudoprogression Discrimination Using Multiparametric Magnetic Resonance Imaging, Principal Component Analysis, and Supervised and Unsupervised Machine Learning," *World Neurosurg.*, vol. 183, pp. e953–e962, Mar. 2024, doi: 10.1016/j.wneu.2024.01.074.

[67] M. H. Mobarak *et al.*, "Scope of machine learning in materials research—A review," *Appl. Surf. Sci. Adv.*, vol. 18, 2023, doi: 10.1016/j.apsadv.2023.100523.

[68] J. Zhao *et al.*, "Battery safety : Machine learning-based prognostics," *Progress in Energy and Combustion Science*, vol. 102, 2024.

[69] O. Alqaryouti, N. Siyam, A. Abdel Monem, and K. Shaalan, "Aspect-based sentiment analysis using smart government review data," *Appl. Comput. Informatics*, vol. 20, no. 1–2, pp. 142–161, 2024, doi: 10.1016/j.aci.2019.11.003.

[70] H. Q. Low, P. Keikhosrokiani, and M. P. Asl, "Decoding violence against women: Analysing harassment in middle eastern literature with machine learning and sentiment analysis," *Humanit. Soc. Sci. Commun.*, vol. 11, no. 1, pp. 1-18, 2024, doi: 10.1057/s41599-024-02908-7.

[71] S. Shaukat, M. Asad, and A. Akram, "Developing an Urdu Lemmatizer Using a Dictionary-Based Lookup Approach," *Appl. Sci.*, vol. 13, no. 8, 2023, doi: 10.3390/app13085103.

[72] T. McEnery, "Review of Egbert, Biber & Gray (2022): Designing and Evaluating Language Corpora: A Practical Framework for Corpus Representativeness," *Int. J. Corpus Linguist.*, vol. 28, no. 4, pp. 586–591, Jul. 2023, doi: 10.1075/ijcl.00054.mce.

[73] X. Tao and V. Aryadoust, "A Multidimensional Analysis of a High-Stakes English Listening Test: A Corpus-Based Approach," *Educ. Sci.*, vol. 14, no. 2, p. 137, Jan. 2024, doi: 10.3390/educsci14020137.

[74] M. Usama, B. Ahmad, E. Song, M. S. Hossain, M. Alrashoud, and G. Muhammad, "Attention-based sentiment analysis using convolutional and recurrent neural network," *Futur. Gener. Comput. Syst.*, vol. 113, pp. 571–578, Dec. 2020, doi: 10.1016/j.future.2020.07.022.

[75] M. Bouazizi and T. Ohtsuki, "Multi-class sentiment analysis on twitter: Classification performance and challenges," *Big Data Min. Anal.*, vol. 2, no. 3, pp. 181–194, Sep. 2019, doi: 10.26599/BDMA.2019.9020002.

[76] H. Huang, A. A. Zavareh, and M. B. Mustafa, "Sentiment Analysis in E-Commerce Platforms: A Review of Current Techniques and Future Directions," *IEEE Access*, vol. 11, pp. 90367–90382, 2023, doi: 10.1109/ACCESS.2023.3307308.

[77] A. D. Cahyani, "Aspect-Based Sentiment Analysis from User-Generated Content in Shopee Marketplace Platform," *J. Ilm. Tek. Elektro Komput. dan Inform.*, vol. 9, no. 2, pp. 444–454, 2023, doi: 10.26555/jiteki.v9i2.26367.

[78] P. Hajek, L. Hikkerova, and J.-M. Sahut, "Fake review detection in e-Commerce platforms using aspect-based sentiment analysis," *J. Bus. Res.*, vol. 167, p. 114143, Nov. 2023, doi: 10.1016/j.jbusres.2023.114143.

[79] A. J. Najafabadi, A. Skryzhadlovska, and O. F. Valilai, "Agile Product Development by Prediction of Consumers' Behaviour; using Neurobehavioral and Social Media Sentiment Analysis Approaches," *Procedia Comput. Sci.*, vol. 232, no. 2023, pp. 1683–1693, 2024, doi: 10.1016/j.procs.2024.01.166.

[80] A. L. Karn *et al.*, *Customer centric hybrid recommendation system for E-Commerce applications by integrating hybrid sentiment analysis*, vol. 23, no. 1. Springer US, 2023, doi: 10.1007/s10660-022-09630-z.

[81] A. El-Ansari and A. Beni-Hssane, "Sentiment Analysis for Personalized Chatbots in E-Commerce Applications," *Wirel. Pers. Commun.*, vol. 129, no. 3, pp. 1623–1644, Apr. 2023, doi: 10.1007/s11277-023-10199-5.

[82] A. H. Khine, W. Wettayaprasit, and J. Duangsuwan, "A new word embedding model integrated with medical knowledge for deep learning-based sentiment classification," *Artif. Intell. Med.*, vol. 148, p. 102758, Feb. 2024, doi: 10.1016/j.artmed.2023.102758.

[83] K. K. Agustiningsih, E. Utami, and O. M. A. Alsyaibani, "Sentiment Analysis and Topic Modelling of The COVID-19 Vaccine in Indonesia on Twitter Social Media Using Word Embedding," *J. Ilm. Tek. Elektro Komput. dan Inform.*, vol. 8, no. 1, p. 64, 2022, doi: 10.26555/jiteki.v8i1.23009.

[84] T. Ahammad, "Identifying hidden patterns of fake COVID-19 news: An in-depth sentiment analysis and topic modeling approach," *Nat. Lang. Process. J.*, vol. 6, p. 100053, 2024, doi: 10.1016/j.nlp.2024.100053.

[85] A. Çiçek Korkmaz, "Public's perception on nursing education during the COVID-19 pandemic: SENTIMENT analysis of Twitter data," *Int. J. Disaster Risk Reduct.*, vol. 99, p. 104127, Dec. 2023, doi: 10.1016/j.ijdrr.2023.104127.

[86] A. R. Pratama, "Sentiment Analysis of Facebook Posts through Special Reactions: The Case of Learning from Home in Indonesia Amid COVID-19," *J. Ilm. Tek. Elektro Komput. dan Inform.*, vol. 8, no. 1, p. 83, 2022, doi: 10.26555/jiteki.v8i1.23615.

[87] M. Ramzy and B. Ibrahim, "User satisfaction with Arabic COVID-19 apps: Sentiment analysis of users' reviews using machine learning techniques," *Inf. Process. Manag.*, vol. 61, no. 3, p. 103644, May 2024, doi: 10.1016/j.ipm.2024.103644.

[88] J. Zhou and J. Ye, "Sentiment analysis in education research: a review of journal publications," *Interact. Learn. Environ.*, vol. 31, no. 3, pp. 1252–1264, Apr. 2023, doi: 10.1080/10494820.2020.1826985.

[89] M. Alassaf and A. M. Qamar, "Improving Sentiment Analysis of Arabic Tweets by One-way ANOVA," *J. King Saud Univ. - Comput. Inf. Sci.*, vol. 34, no. 6, pp. 2849–2859, 2022, doi: 10.1016/j.jksuci.2020.10.023.

[90] P. SV and V. S, "Critique of the paper, 'Public's perception on nursing education during the COVID-19 Pandemic: Sentiment Analysis of Twitter Data,'" *Int. J. Disaster Risk Reduct.*, vol. 101, p. 104232, Feb. 2024, doi: 10.1016/j.ijdrr.2023.104232.

[91] T. Shaik, X. Tao, C. Dann, H. Xie, Y. Li, and L. Galligan, "Sentiment analysis and opinion mining on educational data: A survey," *Nat. Lang. Process. J.*, vol. 2, p. 100003, Mar. 2023, doi: 10.1016/j.nlp.2022.100003.

[92] D. K. Dake and E. Gyimah, "Using sentiment analysis to evaluate qualitative students' responses," *Educ. Inf. Technol.*, vol. 28, no. 4, pp. 4629–4647, 2023, doi: 10.1007/s10639-022-11349-1.

[93] M. Usart, C. Grimalt-Álvaro, and A. M. Iglesias-Estradé, "Gender-sensitive sentiment analysis for estimating the emotional climate in online teacher education," *Learn. Environ. Res.*, vol. 26, no. 1, pp. 77–96, 2023, doi: 10.1007/s10984-022-09405-1.

[94] Y. P. Mulyani *et al.*, "Analyzing public discourse on photovoltaic (PV) adoption in Indonesia: A topic-based sentiment analysis of news articles and social media," *J. Clean. Prod.*, vol. 434, 2024, doi: 10.1016/j.jclepro.2023.140233.

[95] S. Zhou *et al.*, "Revealing Public Attitudes toward Mobile Cabin Hospitals during Covid-19 Pandemic: Sentiment and Topic Analyses Using Social Media Data in China," *Sustain. Cities Soc.*, p. 105440, Apr. 2024, doi: 10.1016/j.scs.2024.105440.

[96] Z. Li and Z. Zou, "Punctuation and lexicon aid representation: A hybrid model for short text sentiment analysis on social media platform," *J. King Saud Univ. - Comput. Inf. Sci.*, vol. 36, no. 3, p. 102010, 2024, doi: 10.1016/j.jksuci.2024.102010.

[97] V. S. Anoop, C. Subin Krishna, and U. H. Govindarajan, "Graph embedding approaches for social media sentiment analysis with model explanation," *Int. J. Inf. Manag. Data Insights*, vol. 4, no. 1, 2024, doi: 10.1016/j.jjimei.2024.100221.

[98] M. Ashayeri and N. Abbasabadi, "Unraveling energy justice in NYC urban buildings through social media sentiment analysis and transformer deep learning," *Energy Build.*, vol. 306, p. 113914, Mar. 2024, doi: 10.1016/j.enbuild.2024.113914.

[99] H. L. Nisa and A. Ahdika, "Hybrid Method for User Review Sentiment Categorization in ChatGPT Application Using N-Gram and Word2Vec Features," *Knowl. Eng. Data*, vol. 7, no. 1, pp. 13–26, 2024.

[100] M. Y. Chuttur and Y. Parianen, "A Comparison of Machine Learning Models to Prioritise Emails using Emotion Analysis for Customer Service Excellence," *Knowl. Eng. Data Sci.*, vol. 5, no. 1, p. 41, 2022, doi: 10.17977/um018v5i12022p41-52.

[101] Z. A. Diekson, M. R. B. Prakoso, M. S. Q. Putra, M. S. A. F. Syaputra, S. Achmad, and R. Sutoyo, "Sentiment analysis for customer review: Case study of Traveloka," *Procedia Comput. Sci.*, vol. 216, pp. 682–690, 2023, doi: 10.1016/j.procs.2022.12.184.

[102] P. Savci and B. Das, "Prediction of the customers' interests using sentiment analysis in e-commerce data for comparison of Arabic, English, and Turkish languages," *J. King Saud Univ. - Comput. Inf. Sci.*, vol. 35, no. 3, pp. 227–237, 2023, doi: 10.1016/j.jksuci.2023.02.017.

[103] N. Pleerux and A. Nardkulpat, "Sentiment analysis of restaurant customer satisfaction during COVID-19 pandemic in Pattaya, Thailand," *Heliyon*, vol. 9, no. 11, 2023, doi: 10.1016/j.heliyon.2023.e22193.

[104] A. Patel, P. Oza, and S. Agrawal, "Sentiment Analysis of Customer Feedback and Reviews for Airline Services using Language Representation Model," *Procedia Comput. Sci.*, vol. 218, pp. 2459–2467, 2023, doi: 10.1016/j.procs.2023.01.221

[105] S. Jardim and C. Mora, "Customer reviews sentiment-based analysis and clustering for market-oriented tourism services and products development or positioning," *Procedia Comput. Sci.*, vol. 196, no. 2021, pp. 199–206, 2021, doi: 10.1016/j.procs.2021.12.006.

[106] A. Karami and A. Elkouri, "Political Popularity Analysis in Social Media," in *Information in Contemporary Society*, vol. 11420, pp. 456–465, 2019, doi: 10.1007/978-3-030-15742-5_44.

[107] A. Sharma and U. Ghose, "Sentimental Analysis of Twitter Data with respect to General Elections in India," *Procedia Comput. Sci.*, vol. 173, pp. 325–334, 2020, doi: 10.1016/j.procs.2020.06.038.

[108] D. Antypas, A. Preece, and J. Camacho-Collados, "Negativity spreads faster: A large-scale multilingual twitter analysis on the role of sentiment in political communication," *Online Soc. Networks Media*, vol. 33, 2023, doi: 10.1016/j.osnem.2023.100242.

[109] A. Karami *et al.*, "2020 U.S. presidential election in swing states: Gender differences in Twitter conversations," *Int. J. Inf. Manag. Data Insights*, vol. 2, p. 100097, 2022, doi: 10.1016/j.jjimei.2022.100097.

[110] M. M. Skoric, J. Liu, and K. Jaidka, "Electoral and public opinion forecasts with social media data: A meta-analysis," *Inf.*, vol. 11, no. 4, pp. 1–17, 2020, doi: 10.3390/info11040187.

[111] K. Brito and P. J. L. Adeodato, "Machine learning for predicting elections in Latin America based on social media engagement and polls," *Gov. Inf. Q.*, vol. 40, no. 1, p. 101782, Jan. 2023, doi: 10.1016/j.giq.2022.101782.

[112] O. Alsemaree, A. S. Alam, S. Gill, and S. Uhlig, "Sentiment analysis of Arabic social media texts: A machine learning approach to deciphering customer perceptions," *Heliyon*, p. e27863, Mar. 2024, doi: 10.1016/j.heliyon.2024.e27863.

[113] P. Y. Win Myint, S. L. Lo, and Y. Zhang, "Unveiling the dynamics of crisis events: Sentiment and emotion analysis via multi-task learning with attention mechanism and subject-based intent prediction," *Inf. Process. Manag.*, vol. 61, no. 4, 2024, doi: 10.1016/j.ipm.2024.103695.

[114] N. Das, B. Sadhukhan, R. Chatterjee, and S. Chakrabarti, "Integrating sentiment analysis with graph neural networks for enhanced stock prediction: A comprehensive survey," *Decis. Anal. J.*, vol. 10, 2024, doi: 10.1016/j.dajour.2024.100417.

[115] M. Li and Y. Shi, "Sentiment analysis and prediction model based on Chinese government affairs microblogs," *Heliyon*, vol. 9, no. 8, 2023, doi: 10.1016/j.heliyon.2023.e19091.

[116] C. Haas, C. Budin, and A. d'Arcy, "The Effect of Performance Metrics and Sentiment Scores on Selecting Oil Price Prediction Models," *SSRN Electron. J.*, vol. 133, 2022, doi: 10.2139/ssrn.4252441.

[117] P. Mukherjee, Y. Badr, S. Doppalapudi, S. M. Srinivasan, R. S. Sangwan, and R. Sharma, "Effect of Negation in Sentences on Sentiment Analysis and Polarity Detection," *Procedia Comput. Sci.*, vol. 185, pp. 370–379, 2021, doi: 10.1016/j.procs.2021.05.038.

[118] P. F. Muhammad, R. Kusumaningrum, and A. Wibowo, "Sentiment Analysis Using Word2vec and Long Short-Term Memory (LSTM) for Indonesian Hotel Reviews," *Procedia Comput. Sci.*, vol. 179, pp. 728–735, 2021, doi: 10.1016/j.procs.2021.01.061.

[119] H. Y. Lin and T. S. Moh, "Sentiment analysis on COVID tweets using COVID-Twitter-BERT with auxiliary sentence approach," *Proc. 2021 ACMSE Conf. - ACMSE 2021 Annu. ACM Southeast Conf.*, pp. 234–238, 2021, doi: 10.1145/3409334.3452074.

[120] P. Shah, P. Swaminarayan, and M. Patel, "Sentiment analysis on film review in Gujarati language using machine learning," *International Journal of Electrical and Computer Engineering*, vol. 12, no. 1, pp. 1030–1039, 2022. doi: 10.11591/ijece.v12i1.pp1030-1039.

[121] C. Ahmed, A. ElKorany, and E. ElSayed, "Prediction of customer's perception in social networks by integrating sentiment analysis and machine learning," *J. Intell. Inf. Syst.*, vol. 60, no. 3, pp. 829–851, 2023, doi: 10.1007/s10844-022-00756-y.

[122] M. Qorib, T. Oladunni, M. Denis, E. Ososanya, and P. Cotae, "Covid-19 vaccine hesitancy: Text mining, sentiment analysis and machine learning on COVID-19 vaccination Twitter dataset," *Expert Syst. Appl.*, vol. 212, p. 118715, Feb. 2023, doi: 10.1016/j.eswa.2022.118715.

[123] A. Vohra and R. Garg, "Deep learning based sentiment analysis of public perception of working from home through tweets," *J. Intell. Inf. Syst.*, vol. 60, no. 1, pp. 255–274, 2023, doi: 10.1007/s10844-022-00736-2.

[124] K. Hayawi, S. Shahriar, M. A. Serhani, I. Taleb, and S. S. Mathew, "ANTi-Vax: a novel Twitter dataset for COVID-19 vaccine misinformation detection," *Public Health*, vol. 203, pp. 23–30, 2022, doi: 10.1016/j.puhe.2021.11.022.

[125] T. Wegderes, M. Million, H. Ashebir, and L. Kedir, "Sentiment Mining and Aspect Based Summarization of Opinionated Afaan Sentiment Mining and Aspect Based Summarization of Opinionated Afaan Oromoo News Text," vol. 9, pp. 66–72, 2022, doi: 10.11648/j.ajesa.20220902.12.

[126] D. Anusic and A. Hussain, "Listen to the noise Demonstrating an end to end multi-platform and multilingual sentiment analysis approach," *Procedia Comput. Sci.*, vol. 219, pp. 546–553, 2023, doi: 10.1016/j.procs.2023.01.323.

[127] K. Sarkar, "Sentiment polarity detection in Bengali tweets using LSTM recurrent neural networks," *2019 2nd Int. Conf. Adv. Comput. Commun. Paradig. ICACCP 2019*, vol. 28, no. 3, pp. 377–386, 2019, doi: 10.1109/ICACCP.2019.8883010.

[128] K. R. Mabokela, T. Celik, and M. Raborife, "Multilingual Sentiment Analysis for Under-Resourced Languages: A Systematic Review of the Landscape," *IEEE Access*, vol. 11, pp. 15996–16020, 2023, doi: 10.1109/ACCESS.2022.3224136.

[129] R. K. Das, M. Islam, M. M. Hasan, S. Razia, M. Hassan, and S. A. Khushbu, "Sentiment analysis in multilingual context: Comparative analysis of machine learning and hybrid deep learning models," *Heliyon*, vol. 9, no. 9, pp. 1–20, 2023, doi: 10.1016/j.heliyon.2023.e20281.

[130] E. Zuo, H. Zhao, B. Chen, and Q. Chen, "Context-Specific Heterogeneous Graph Convolutional Network for Implicit Sentiment Analysis," *IEEE Access*, vol. 8, pp. 37967–37975, 2020, doi: 10.1109/ACCESS.2020.2975244.

[131] S. Kaddoura and R. Nassar, "EnhancedBERT: A feature-rich ensemble model for Arabic word sense disambiguation with statistical analysis and optimized data collection," *J. King Saud Univ. - Comput. Inf. Sci.*, vol. 36, no. 1, 2024, doi: 10.1016/j.jksuci.2023.101911.

[132] H. Grissette and E. H. Nfaoui, "Semisupervised neural biomedical sense disambiguation approach for aspect-based sentiment analysis on social networks," *J. Biomed. Inform.*, vol. 135, 2022, doi: 10.1016/j.jbi.2022.104229.

[133] A. Shaik, N. Tondehal, and V. Lavudya, "A study on problematic Internet use associated with social anxiety among medical students.," *Int. J. Surg. Med.*, vol. 9, p. 1, 2023, doi: 10.5455/ijsm.136-1662136136.

[134] Q. A. Xu, C. Jayne, and V. Chang, "An emoji feature-incorporated multi-view deep learning for explainable sentiment classification of social media reviews," *Technol. Forecast. Soc. Change*, vol. 202, 2024, doi: 10.1016/j.techfore.2024.123326.

[135] G. Caldarelli, R. De Nicola, F. Del Vigna, M. Petrocchi, and F. Saracco, "The role of bot squads in the political propaganda on Twitter," *Commun. Phys.*, vol. 3, no. 1, 2020, doi: 10.1038/s42005-020-0340-4.

[136] R. P. Pratama and A. Tjahyanto, "The influence of fake accounts on sentiment analysis related to COVID-19 in Indonesia," *Procedia Comput. Sci.*, vol. 197, pp. 143–150, 2021, doi: 10.1016/j.procs.2021.12.128.

[137] J. Pastor-Galindo *et al.*, "Spotting Political Social Bots in Twitter: A Use Case of the 2019 Spanish General Election," *IEEE Trans. Netw. Serv. Manag.*, vol. 17, no. 4, pp. 2156–2170, Dec. 2020, doi: 10.1109/TNSM.2020.3031573.

[138] R. Schuchard, A. T. Crooks, A. Stefanidis, and A. Croitoru, "Bot stamina: examining the influence and staying power of bots in online social networks," *Appl. Netw. Sci.*, vol. 4, no. 1, 2019, doi: 10.1007/s41109-019-0164-x.

[139] R. J. Schuchard and A. T. Crooks, "Insights into elections: An ensemble bot detection coverage framework applied to the 2018 U.S. midterm elections," *PLoS One*, vol. 16, no. 1, p. e0244309, Jan. 2021, doi: 10.1371/journal.pone.0244309.

[140] Y. Gorodnichenko, T. Pham, and O. Talavera, "Social media, sentiment and public opinions: Evidence from #Brexit and #USElection," *Eur. Econ. Rev.*, vol. 136, p. 103772, Jul. 2021.