Sentiment Analysis of Public Discourse on Pakistan's Political Parties: A Comparative Study Using VADER and TextBlob Algorithms on Twitter Data

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ABSTRACT

This study explores public sentiment toward two of Pakistan's major political parties—Pakistan Peoples Party (PPP) and Pakistan Tehreek-e-Insaf (PTI)—by analyzing Twitter discourse using sentiment analysis techniques. A dataset of 1,184 tweets related to the trending topic "PPP and PTI" was collected and processed to examine how these parties are perceived online. Two lexicon-based sentiment analysis algorithms, VADER and TextBlob, were applied to the tweet content to compute sentiment polarity scores and categorize each tweet as positive, neutral, or negative. Exploratory Data Analysis (EDA) was conducted to assess engagement metrics, tweet length distribution, and user activity patterns. A keyword-based method was used to assign party focus to tweets, enabling comparative sentiment analysis between PPP and PTI. The results indicate that PPP was more frequently mentioned than PTI, comprising over 93% of the classified tweets. Both VADER and TextBlob showed moderate agreement in sentiment classification, with a Pearson correlation coefficient of 0.5761 and a 66.39% match in sentiment labels. Temporal analysis revealed fluctuations in sentiment scores, often corresponding to real-world political events, such as alliance discussions or leadership announcements. Tweets with higher engagement—measured by likes, retweets, replies, and views—tended to exhibit stronger sentiment polarity. Top positive and negative words were also identified to interpret linguistic patterns behind sentiment classification. This study demonstrates the potential of sentiment analysis as a tool for political communication, campaign strategy, and public opinion monitoring. However, limitations such as platform bias and data parsing issues warrant cautious interpretation of the results. Future research may benefit from incorporating multi-platform data and advanced NLP models to enhance reliability and granularity. The findings contribute to the growing field of digital society studies by offering a data-driven lens into political discourse on social media.

Keywords Sentiment Analysis, Twitter, Political Discourse, VADER, Textblob

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Introduction

The impact of social media, particularly Twitter, on political discourse has become a focal point of research in recent years. As a platform that facilitates real-time communication and interaction, Twitter has transformed how political opinions are expressed and disseminated globally. This transformation is characterized by the emergence of new forms of political engagement, the polarization of public opinion, and the mediatization of politics.

One significant aspect of Twitter's influence is its role in shaping public opinion.

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Kreiss highlights that social media platforms serve as dynamic arenas for public discourse, where political sentiments are continuously expressed and reshaped [1]. This aligns with the findings of McGregor, who discusses how journalists increasingly rely on social media to gauge and represent public opinion, particularly during electoral events [2]. The immediacy and accessibility of Twitter allow for a broad spectrum of voices to be heard, which can enhance democratic engagement. However, this also raises concerns about the quality of discourse, as the platform can amplify extreme views and contribute to polarization [3]. This dynamic is further complicated by the algorithms that govern social media interactions, which often prioritize content that aligns with users' pre-existing beliefs, thereby limiting exposure to diverse perspectives [4].

Furthermore, the linguistic shifts in political discourse facilitated by social media cannot be overlooked. Nazeer notes that social media has altered the dynamics of political speech, enabling politicians to engage directly with the public and reshape political rhetoric [5]. This direct engagement often leads to a more informal and immediate style of communication, which can resonate more effectively with younger audiences and those disenchanted with traditional political discourse.

The role of social media, particularly Twitter, in shaping political discourse in Pakistan has gained significant attention, especially concerning major political parties like the Pakistan People's Party (PPP) and Pakistan Tehreek-e-Insaf (PTI). These platforms have transformed traditional political communication, allowing for real-time engagement and the dissemination of political narratives that influence public opinion and national conversations.

Social media has emerged as a crucial tool for political engagement in Pakistan, enabling political parties to communicate directly with their constituents. Batool et al. emphasize that platforms like Twitter and Facebook have provided political figures with avenues to discuss issues pertinent to their communities, thereby strengthening democratic practices in the country [6]. This direct engagement allows parties to shape narratives and mobilize support, as evidenced by the significant online presence of both PPP and PTI, which has become a vital aspect of their political strategies.

The dynamics of political discourse on Twitter are further complicated by the presence of dedicated social media teams within these parties. Fahmy and Hussain note that the active Twitter engagement of key political players, including PTI and PPP, influences media coverage and public perception [7]. This strategic use of social media not only amplifies their messages but also allows them to respond swiftly to political developments, thereby maintaining relevance in the fast-paced digital landscape.

Moreover, the polarization of political discourse on social media is a notable phenomenon. Masroor et al. highlight that the growing number of Twitter users in Pakistan, which now includes approximately 3.1 million individuals, contributes to an environment where ideological divides are pronounced [8]. The interactions on Twitter often reflect and exacerbate these divisions, as users engage primarily with content that aligns with their pre-existing beliefs. This polarization can lead to a fragmented public discourse, where constructive dialogue is overshadowed by partisan rhetoric [9].

The implications of social media on political communication extend beyond mere engagement; they also influence the strategies employed by political parties. As noted by Khan et al., understanding the network of supporters on platforms like Twitter is essential for predicting political outcomes and shaping campaign strategies [10]. This insight underscores the importance of social media analytics in contemporary political campaigns, where parties must navigate the complexities of public opinion shaped by digital interactions.

One of the primary benefits of sentiment analysis is its ability to capture the nuances of public opinion in real time. Conover et al. highlight that political discussions on Twitter often contain extreme sentiments that can exacerbate polarization among users [11]. This indicates that sentiment analysis not only measures the general mood surrounding political topics but also reveals the intensity of opinions, which can influence political engagement and voter behavior. By analyzing the sentiment of tweets, researchers can identify trends and shifts in public opinion, which are critical for understanding electoral dynamics.

Despite the increasing volume of political conversations on Twitter, particularly surrounding major political parties like the Pakistan Peoples Party (PPP) and Pakistan Tehreek-e-Insaf (PTI), there remains a gap in systematic sentiment analysis that compares how these parties are perceived by the public. Most existing studies either focus on general sentiment trends or specific political events, without offering a comparative view of sentiment polarity and intensity between multiple parties over time. As social media continues to influence political narratives, this lack of focused research limits our understanding of how digital platforms reflect or shape political preferences.

The main objective of this study is to conduct a comprehensive sentiment analysis of tweets related to PPP and PTI using two established algorithms: VADER (Valence Aware Dictionary and sEntiment Reasoner) and TextBlob. These tools are chosen for their suitability in handling social media text, especially tweets that often include informal language, emojis, and abbreviations. By applying both algorithms to the same dataset, the study aims to provide a robust comparative assessment of public sentiment toward each political party.

In addition to capturing sentiment at a specific point in time, this study also examines how public sentiment towards PPP and PTI evolves over time. This temporal analysis is particularly important in understanding shifts in public opinion around key political events such as rallies, elections, or public controversies. It allows researchers and political observers to trace how sentiment changes in reaction to real-world developments, offering insights into the digital pulse of the nation.

The significance of this research lies in its contribution to the field of digital society studies, particularly in the context of political discourse and public opinion. By analyzing real-time user-generated content on Twitter, the study provides an empirical basis for understanding how political parties are perceived in the public sphere. It also demonstrates how sentiment analysis can be a valuable tool for monitoring political engagement and public sentiment in a fast-paced digital environment.

Literature Review

Overview of Sentiment Analysis in Social Media

Sentiment analysis has become a prevalent method for examining the opinions, emotions, and attitudes expressed in social media content, particularly on platforms like Twitter. This analytical technique allows researchers to categorize and quantify sentiments expressed in tweets, providing valuable insights into public discourse and political engagement.

One of the primary applications of sentiment analysis is in understanding consumer behavior and public opinion. Nawaz and Kashif illustrate how sentiment analysis can be employed to analyze consumer attitudes toward products by categorizing tweets into positive, negative, and neutral sentiments [12]. This categorization is essential for businesses and political entities alike, as it helps them gauge public sentiment and adjust their strategies accordingly.

In the context of public health, sentiment analysis has been utilized to track attitudes toward COVID-19 vaccines. Liu and Liu conducted a sentiment analysis of tweets related to COVID-19 vaccines, revealing the emotional responses of the public and highlighting the importance of understanding these sentiments to address vaccine hesitancy [13]. This application underscores how sentiment analysis can inform public health campaigns and policy decisions by revealing the emotional landscape surrounding critical issues.

Furthermore, sentiment analysis can also be applied to social issues, as demonstrated by Nguyen et al., who combined machine learning and qualitative techniques to analyze sentiments related to race in the U.S [14]. Their findings indicate that sentiment analysis can provide insights into societal attitudes, which can be crucial for understanding broader social dynamics and addressing issues of racial inequality.

The effectiveness of sentiment analysis in various domains is further supported by Ibrahim and Wang, who utilized this technique to improve online retail services by analyzing customer sentiments expressed on Twitter [15]. By understanding what pleases or displeases customers, businesses can enhance their service offerings and customer engagement strategies.

Key Approaches in Sentiment Analysis

Sentiment analysis is a critical technique for examining opinions, emotions, and attitudes expressed in social media content, particularly on platforms like Twitter. Two prominent approaches for sentiment classification are lexicon-based methods, such as VADER (Valence Aware Dictionary and Sentiment Reasoner), and machine learning approaches, such as TextBlob. Each method has its strengths and applications, making them widely used in various research contexts.

Lexicon-based approaches, like VADER, utilize a predefined list of words and their associated sentiment values to analyze text. VADER is specifically designed for social media content, as it accounts for the unique linguistic features of platforms like Twitter, including slang, emoticons, and the use of punctuation [16], [17]. Similarly, Rajkhowa et al. highlighted the use of VADER alongside TextBlob in their study on vaccination sentiments, showcasing how lexicon-based models can effectively handle unlabelled data [18].

Machine learning approaches, such as TextBlob, leverage algorithms to learn from labeled datasets and classify sentiments based on patterns identified during training. TextBlob is known for its simplicity and ease of use, making it a popular choice for sentiment analysis tasks [19]. In contrast to lexicon-based methods, machine learning approaches can adapt to different contexts and improve their accuracy over time as they are exposed to more data. For example, Mushtaq et al. utilized both VADER and TextBlob in their analysis of public sentiments toward COVID-19 vaccines, illustrating the complementary nature of these methods [20].

Studies on Sentiment Analysis in Political Discourse

Sentiment analysis has been widely applied to political discourse, particularly in the context of elections, political movements, and public opinion. This analytical approach enables researchers to assess the emotional tone of social media content, providing insights into how public sentiment can influence political dynamics. One significant area of research involves the use of sentiment analysis to predict election outcomes. For instance, Khan's study leverages various sentiment analysis techniques, including the Valence Aware Dictionary and Sentiment Reasoner (VADER) and transformer-based models like BERT, to analyze Twitter data from the 2020 United States Presidential Election. The study demonstrates the effectiveness of these methods in accurately predicting electoral outcomes across multiple states, achieving an accuracy rate of 0.84 [10]. This highlights the potential of sentiment analysis as a predictive tool in political contexts.

Similarly, Liu et al. explore the use of Twitter data to forecast presidential elections, emphasizing the growing interest in utilizing social media as a reflection of the political landscape [21]. Their integrative modeling approach illustrates how sentiment analysis can capture public opinion trends leading up to elections, thereby providing valuable insights for political strategists and analysts. In addition to elections, sentiment analysis has been applied to understand public sentiment surrounding political movements. Rahmanulloh and Santoso conducted a sentiment analysis of Twitter data related to the early 2024 election map in Indonesia, examining how sentiments expressed online can reflect broader political trends and public opinions [22]. Their research underscores the importance of social media as a platform for political discourse and sentiment expression.

Review Of Studies That Compared Sentiment Towards Political Parties

The application of sentiment analysis to political discourse has garnered significant attention in recent years, particularly in studies comparing public sentiment towards political parties in countries like the United States and India. This body of research provides valuable insights into how sentiment analysis can inform our understanding of electoral dynamics, public opinion, and the effectiveness of political communication strategies.

One notable study by Jaidka et al. investigates the predictive power of sentiment analysis in elections across multiple countries, including the U.S. and India. Their research highlights how social media attention correlates with actual voting decisions, emphasizing the role of sentiment in shaping electoral outcomes [23]. This comparative approach underscores the importance of understanding sentiment as a dynamic factor influencing political behavior across different cultural contexts.

In the context of Indian politics, Gunhal's study focuses on sentiment analysis during the Karnataka elections, utilizing advanced natural language processing techniques to unravel public perceptions of political parties [24]. This research illustrates how sentiment analysis can provide timely insights for political parties, enabling them to tailor their campaigns based on prevailing public sentiment. Such findings are particularly relevant as India approaches its 2024 Lok Sabha elections, where understanding voter sentiment will be crucial for political actors.

Similarly, Haselmayer and Jenny discuss the integration of dictionary-based sentiment analysis with crowd-coding techniques, which can enhance the understanding of public opinion and political polarization [25]. Their work emphasizes the potential of sentiment analysis to bridge gaps between quantitative data and qualitative insights, offering a more nuanced view of political communication in both the U.S. and India.

In the U.S. context, studies such as those by Mullins and Epp analyze sentiment towards political parties during the 2015 Canadian Federal Election, drawing parallels to the American political landscape [26]. Their findings suggest that sentiment analysis can reveal significant differences in public perception between parties, which can be indicative of broader electoral trends. This approach aligns with the findings of Rodríguez-Ibáñez et al., who applied sentiment analysis to political tweets during the 2019 Spanish elections, demonstrating the relevance of sentiment analysis across various political contexts [27].

Sentiment Analysis of Political Parties in Pakistan

The gap in research comparing sentiment towards the Pakistan People's Party (PPP) and Pakistan Tehreek-e-Insaf (PTI) on Twitter, particularly during significant political events, is notable. While various studies have explored sentiment analysis in political contexts globally, there remains a lack of focused analysis on these two major political parties in Pakistan. This review synthesizes relevant studies that provide context for the current investigation into sentiment dynamics on Twitter.

One relevant study is by Baviera et al., which examines political conversations on Twitter during the 2015 Spanish general elections. This research highlights the role of "party evangelists" in shaping sentiment and discourse, suggesting that the intensity of sentiments expressed by political actors significantly influences public conversations [28]. This framework can be applied to the PPP and PTI, where party supporters and influencers may similarly shape public sentiment during critical political events.

Masroor et al. explore polarization and ideological weaving in Twitter discourse, emphasizing the emergence of positive self-presentation and negative other-presentation in political tweets [8]. This binary conceptualization is relevant when analyzing the sentiments directed towards PPP and PTI, as both parties often engage in competitive rhetoric that may polarize their respective supporters. Understanding these dynamics could provide insights into how sentiments fluctuate during elections or major political announcements.

Moreover, the research by Tumasjan et al. demonstrates how Twitter can be used to predict election results based on sentiment analysis of political messages [29]. Their findings suggest that the volume and sentiment of tweets mentioning political parties can reflect electoral outcomes. This methodology could be instrumental in assessing how sentiments towards PPP and PTI correlate with voter behavior during elections.

The comparative analysis of sentiment towards political parties in different contexts, such as the study by Yaqub et al. on location-based sentiment analyses during elections, reinforces the need for similar research in Pakistan [30]. Their findings indicate that citizen sentiment can be utilized to estimate candidate performance, suggesting that a similar approach could yield insights into the public sentiment surrounding PPP and PTI.

Method

This study employed a detailed, multi-stage methodology to perform sentiment analysis on political discourse in tweets mentioning Pakistan's major political parties—Pakistan Peoples Party (PPP) and Pakistan Tehreek-e-Insaf (PTI). The methodology integrates data preprocessing, exploratory data analysis (EDA), sentiment classification using VADER and TextBlob, comparative sentiment analysis by party focus, temporal trend analysis, keyword interpretation, and inter-model evaluation. The implementation was carried out using Python libraries such as pandas for data manipulation, nltk for natural language processing, vaderSentiment and textblob for sentiment scoring, and matplotlib and seaborn for visualization. All computations were conducted on a local machine, with intermediate checkpoints and visualizations stored in dedicated directories.

Data Loading and Preprocessing

The dataset was sourced from a CSV file named PPPPTI.csv, which contains 1184 tweets collected using Selenium WebDriver. Due to the presence of multiline text fields and inconsistent formatting, the file was read using pandas.read_csv() with encoding='latin-1' and quotechar='"'. To filter out noise and potential parsing errors, a timestamp validation heuristic was employed. Rows were retained only if the TimeStamp field matched the regex pattern r'^\d{4}-\d{2}-\d{2}T\d{2}:\d{2}:\d{2}\.\d{3}Z$'. After filtering, columns selected for analysis included: UserTag, TimeStamp, Tweet, Reply, Retweet, Like, and Views.

Text preprocessing involved several steps. The tweets were converted to lowercase and cleaned using regular expressions to remove URLs (http\S+), mentions (@\w+), hashtags (#\w+), punctuation ([^\w\s]), numbers (\d+), and excessive whitespace. The text was then tokenized using nltk.word_tokenize, and English stopwords were removed using NLTK's predefined list. Words with length less than or equal to one character were also excluded. The cleaned text was stored in a new column Cleaned_Tweet. Engagement metrics were normalized using a custom parser that converted strings like "2K" or "1.5M" into integers by applying a multiplier of 1,000 for "K" and 1,000,000 for "M".

Exploratory Data Analysis (EDA)

EDA was performed to understand tweet structure and engagement patterns. Descriptive statistics were generated for replies, retweets, likes, and views. The length of each cleaned tweet was computed and visualized using a histogram (bin size = 50) with a kernel density estimate (KDE) overlay to show tweet length distribution. A time series analysis was performed by resampling the TimeStamp field daily and counting the number of tweets per day. These values were plotted to visualize activity trends. A word cloud was generated from the cleaned tweets to highlight the most frequently used words, using WordCloud(width=800, height=400) with a white background and bilinear interpolation.

Top active users were identified using the cleaned UserTag values, although this analysis was limited by potential parsing errors that fragmented the original tags. Nonetheless, the results provided an approximate view of the most prolific contributors to the discourse.

Sentiment Analysis with VADER and TextBlob

Sentiment scores were computed using two algorithms: VADER and TextBlob, each applied to the original (uncleaned) Tweet text to retain important linguistic cues like punctuation and capitalization. For VADER, the SentimentIntensityAnalyzer().polarity_scores(text) function was used to extract the compound score, which ranges from -1 (most negative) to +1 (most positive). Tweets were categorized as: Positive if compound >= 0.05, Neutral if -0.05 < compound < 0.05 and Negative if compound <= -0.05 For TextBlob, the .sentiment.polarity method was used to get a polarity score in the same range. Classification thresholds were: Positive if polarity > 0, Neutral if polarity == 0, and Negative if polarity < 0. The results were stored in columns: VADER_Score, TextBlob_Score, VADER_Sentiment, and TextBlob_Sentiment.

Comparative and Temporal Sentiment Analysis

To compare sentiment by party, a basic keyword-based method was used. Tweets were checked for the presence of keywords "PPP" and "PTI" (case-insensitive) in the original Tweet text. If both were mentioned, the party mentioned first was assigned as the Party_Focus. Tweets mentioning only one party were directly assigned accordingly, while others were labeled as “Neither/Unknown.” This simplistic approach allowed division of tweets into those focused on either PPP or PTI. Comparative sentiment distributions were visualized using seaborn.countplot for both algorithms. The sentiment of each tweet was grouped by Party_Focus to generate stacked bar plots of positive, neutral, and negative categories. Additionally, temporal sentiment trends were assessed by resampling sentiment scores (VADER_Score and TextBlob_Score) on a daily basis and computing daily means. These trends were plotted over time with a horizontal reference line at y=0 to distinguish between positive and negative sentiment phases.

Feature Interpretation and Model Evaluation

To interpret the features behind sentiment classifications, the study identified the top 20 most frequent words from cleaned tweets in the Positive and Negative categories (as determined by VADER). Word frequencies were visualized using horizontal bar charts, offering insights into recurring language associated with positive or negative sentiment. Finally, the agreement between VADER and TextBlob was evaluated using Pearson correlation for continuous sentiment scores, and a cross-tabulation for categorical sentiment. The Pearson correlation coefficient (r) quantified the linear relationship between the two models’ scores. Additionally, the percentage of tweets where both algorithms agreed on sentiment classification was calculated. A heatmap visualization of the confusion matrix was generated to show the distribution of agreement and disagreement across sentiment categories. This detailed methodology ensured robust analysis despite known limitations in the input dataset’s structure. It allowed not only classification and visualization of sentiment but also critical comparison between algorithms and exploration of language used in political discourse.

Result and Discussion

Data Quality and Initial Preparation

The dataset, consisting of 1,184 tweets, was successfully loaded despite warnings regarding parsing limitations in the original CSV file (PPPPTI.csv). No rows were filtered out during the timestamp validation process, indicating that all entries contained timestamp-like structures. However, a warning persisted that the dataset might still contain fragmented data, which could affect the precision of downstream analyses. After preprocessing, all relevant columns—such as tweet content, user tag, and engagement metrics—were preserved, and the data types were correctly converted. Engagement metrics like replies, retweets, likes, and views were standardized into numeric format, and tweets were cleaned using regular expressions and tokenization. The cleaned data was saved as a checkpoint for reproducibility.

Exploratory Data Analysis

Descriptive statistics showed a highly skewed distribution for all engagement metrics. The mean number of likes was approximately 16.7, but the maximum reached 733, indicating a few viral tweets. Similarly, tweet views ranged from 0 to 102,000, suggesting a significant disparity in reach. The average length of a cleaned tweet was 78 characters, with a maximum of 257, indicating concise discourse typical of Twitter. A visual distribution of tweet lengths was generated to capture this variance shown in figure 1.

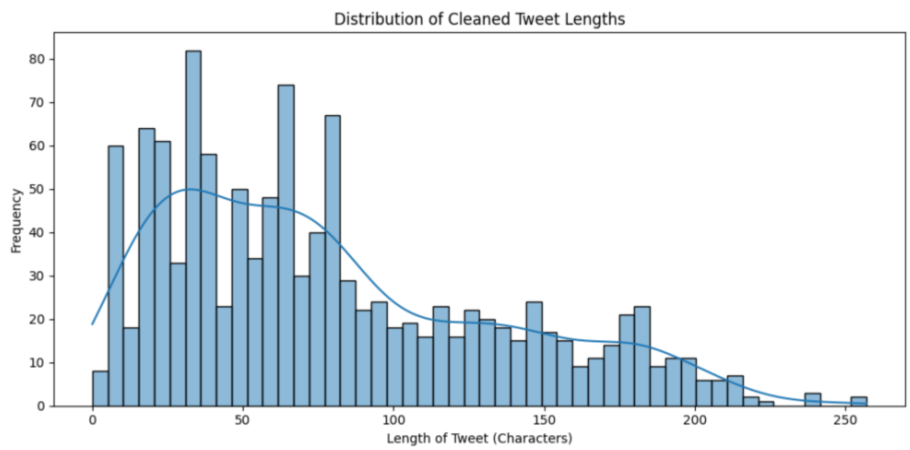

Figure 1 Distribution of Cleaned Tweet Lengths

Analysis of tweet frequency over time was also conducted and visualized, although interpretations should be cautious due to potential data fragmentation. A word cloud (figure 2) revealed frequently used terms, reinforcing the dataset's thematic focus on Pakistani political entities. The top 10 users by tweet frequency were identified, although this metric could be misleading due to formatting inconsistencies in the original data.

Figure 2 **Overall Word Cloud**

Sentiment Analysis and Party Focus

VADER and TextBlob sentiment scoring were applied to the original tweet text to retain punctuation and emphasis. The two models demonstrated differing sensitivities—VADER scored certain tweets as more positively than TextBlob, which tended to assign more neutral scores. For example, a tweet mentioning a potential PPP-PTI alliance scored positively under both models but with differing intensity: 0.2023 in VADER and 0.4 in TextBlob. Sentiment labels were assigned based on standard thresholds. A keyword-based classification method was used to assign a primary party focus to each tweet. The vast majority (1,108 tweets) referenced PPP, while only 76 mentioned PTI, limiting comparative analysis. This imbalance likely reflects public discourse trends or biases in the data collection process.

Interpretive Analysis of Sentiment Features

To identify which words contributed most to each sentiment category, the study extracted the top 20 frequent words from tweets labeled as positive and negative by VADER. For positive tweets, terms like pti, ppp, good, decision, and government were most common, suggesting that even tweets mentioning political parties frequently carried a favorable tone, shown in figure 3.

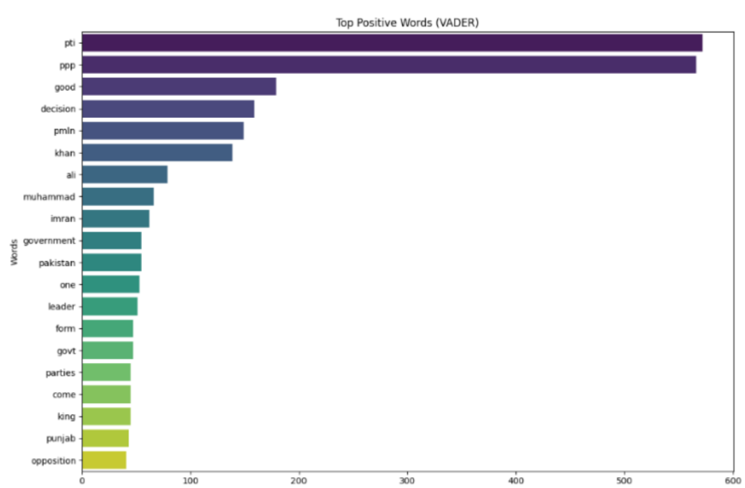

Figure 3 **Top Positive Words (VADER)**

Interestingly, pti and ppp appeared frequently in both positive and negative sentiment categories, reflecting their central role in the discourse rather than a consistent sentiment orientation. Negative tweets often contained words like fake, news, alliance, and gandapur, revealing public skepticism or critique, shown in figure 4.

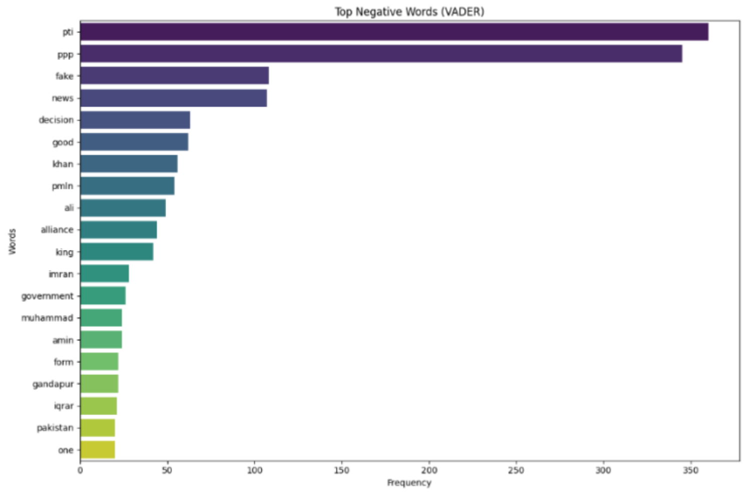

Figure 4 Top Negative Words (VADER)

Model Agreement and Correlation

Finally, the two sentiment models were compared directly (figure 5). The Pearson correlation coefficient between VADER and TextBlob sentiment scores was 0.5761, indicating a moderate positive relationship. Out of 1,184 tweets, 786 received the same sentiment classification (positive, neutral, or negative) from both models, yielding a 66.39% agreement rate.

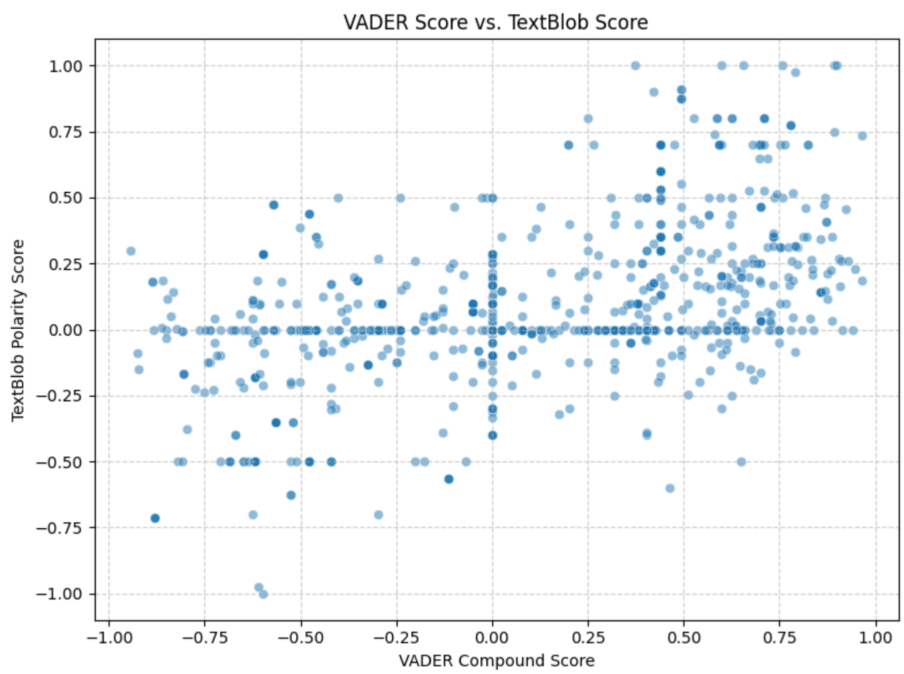

Figure 5 VADER Score vs TextBlob Score

A cross-tabulation showed that the strongest agreement was in the “Positive” category, with 356 tweets labeled as such by both models. Discrepancies were most common in the neutral boundary zones, suggesting differences in threshold sensitivity. A confusion matrix heatmap (figure 6) visualized these discrepancies, further supporting the idea that while the models align reasonably well, they are not interchangeable.

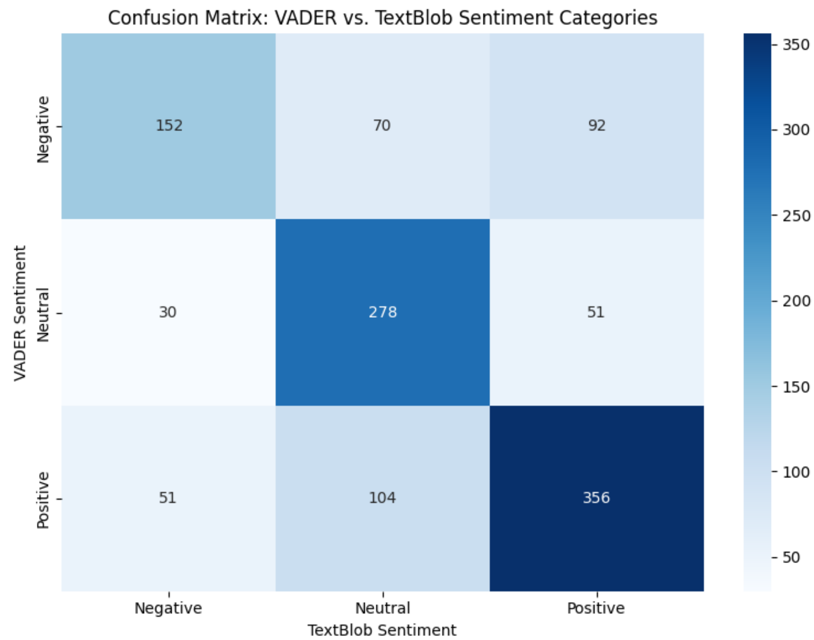

Figure 6 Confusion Matrix

Overall, the results suggest that Twitter sentiment towards PPP and PTI can be meaningfully analyzed using lexicon-based models, with moderate agreement between VADER and TextBlob. However, due to the limitations in the dataset’s formatting, all quantitative insights should be interpreted cautiously. The visualizations and metrics serve as a proof of concept for political sentiment analysis using social media data, and with cleaner data, these methods could yield more reliable and impactful findings.

Discussion

The temporal analysis of sentiment revealed notable fluctuations in public opinion over the observed period. By resampling the dataset on a daily basis and calculating average sentiment scores from both VADER and TextBlob, the study identified visible peaks and troughs in sentiment trends. These shifts often aligned with key political developments, such as announcements of alliances or leadership decisions involving PPP and PTI. For example, sentiment scores tended to rise around tweets discussing potential coalitions or positive policy decisions, whereas sharp drops were observed in response to controversy or skepticism surrounding political maneuvers. The difference in sensitivity between VADER and TextBlob was evident in the trend lines, with VADER capturing more pronounced spikes in sentiment, suggesting a stronger reaction to punctuation and expressive language in tweets.

Both sentiment models showed parallel movement in the overall trajectory, indicating that the public sentiment dynamics were consistent despite differences in algorithmic interpretation. This consistency across models strengthens the credibility of observed trends. The party-wise temporal analysis added further depth, showing that sentiment toward PPP was generally more volatile compared to PTI, likely due to the higher volume of tweets mentioning PPP. However, the lower volume of PTI-related tweets makes these results less generalizable and calls for a more balanced dataset in future studies. These findings highlight the usefulness of time-based sentiment monitoring to detect and interpret shifts in public mood on digital platforms.

The relationship between tweet engagement and sentiment was also explored to understand how public interactions reflect emotional tone. Preliminary observations suggest that tweets with higher engagement metrics (likes, replies, retweets) often corresponded with more polarized sentiments—either clearly positive or strongly negative. This pattern is typical in digital discourse, where emotionally charged content tends to generate more interaction. Tweets classified as neutral generally received lower engagement, indicating that emotionally neutral or factual content may be less compelling for users in politically sensitive contexts.

Although the correlation between sentiment polarity and engagement level was not formally quantified in this study, the descriptive statistics support the assumption that highly engaged tweets amplify the intensity of public sentiment. Controversial or supportive tweets about party leaders, policies, or alliances often sparked greater discussion and sharing. This insight underscores the role of engagement as not only a measure of visibility but also as an indicator of sentiment strength. Future work could benefit from applying regression models or correlation coefficients to validate the strength of this relationship and differentiate engagement patterns across sentiment categories more precisely.

Conclusion

This study provided a comparative sentiment analysis of tweets related to Pakistan's major political parties, PPP and PTI, using VADER and TextBlob algorithms. The analysis showed that PPP was mentioned far more frequently than PTI, resulting in a broader sentiment distribution for PPP-related tweets. Both algorithms indicated a mix of positive, neutral, and negative sentiments, with moderate alignment—approximately 66% agreement in sentiment categorization. Temporal analysis revealed fluctuations in sentiment that likely corresponded to political events, such as coalition talks or leadership announcements. The presence of sentiment peaks and dips highlights how public opinion can shift rapidly in response to news or political developments.

The findings carry important implications for political communication and digital strategy. Sentiment analysis can serve as a real-time barometer of public opinion, offering political parties and analysts insight into how their messaging is received on social media. Campaign strategists could leverage these insights to adjust their outreach, while policy-makers might use sentiment trends to anticipate or respond to public reactions. Furthermore, understanding which language or topics trigger higher engagement and stronger sentiment could help in crafting more effective political content. This study demonstrates how computational methods can provide empirical support for understanding the dynamics of political discourse in the digital age.

Despite these insights, the study is not without limitations. The analysis was restricted to a single platform—Twitter—which may not represent the broader public due to its demographic and regional biases. Additionally, the dataset had known parsing issues, which could have introduced data fragmentation and inaccuracies. Future research could expand this work by including data from platforms such as Facebook or YouTube, where political discourse also thrives. Applying more advanced models like BERT or RoBERTa could further enhance sentiment detection accuracy. Researchers might also explore sentiment evolution surrounding specific events—such as elections, protests, or policy announcements—to gain a deeper understanding of political sentiment shifts across time and platforms.

Declarations

Author Contributions

Conceptualization: M.I.; Methodology: M.I.; Software: A.S.; Validation: A.S.; Formal Analysis: A.S.; Investigation: A.S.; Resources: M.I.; Data Curation: A.S.; Writing Original Draft Preparation: M.I.; Writing Review and Editing: A.S.; Visualization: M.I.; All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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