International Journal Software Engineering and Computer Science (IJSECS)
6 (2), 2026, 829-842
Published Online August 2026 in IJSECS (http://www.journal.lembagakita.com/index.php/ijsecs)
P-ISSN: 2776-4869, E-ISSN: 2776-3242. DOI: https://doi.org/10.35870/ijsecs.v6i2.7524.

RESEARCH ARTICLE Open Access

Exploring the Relationship Between Coordinated Political Communication Activities and Public Sentiment on Platform X Through an Integrated Data Analytics Framework During the First 100 Days of the Prabowo Administration

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Received: June 12, 2026; Accepted: July 25, 2026; Published: August 1, 2026.

Abstract: The rapid growth of social media has transformed political communication patterns in Indonesia, particularly on platform X, which has become an important medium for public opinion formation and digital political discourse. This study aims to examine the relationship between coordinated account activities and public sentiment regarding the performance of President Prabowo Subianto's government during the first 100 working days of his administration. A quantitative data analytics approach was employed using 10,000 public posts collected from platform X between October 20, 2024, and January 29, 2025. The study combined text mining, sentiment analysis, social network analysis, and statistical analysis to identify dominant narratives, sentiment distribution, coordinated account activity patterns, and their relationship with public sentiment. The results showed that the dominant narratives focused on the Free Nutritious Meal Program, public satisfaction, and corruption eradication. Sentiment analysis indicated that 62% of the posts were classified as positive, while social network analysis identified centralized interaction patterns among accounts classified as political buzzers. Statistical analysis showed a significant positive relationship between buzzer activity and positive sentiment, with a Pearson correlation coefficient of 0.78 ($p < 0.01$). Linear regression analysis further indicated that posting frequency, hashtag quantity, and retweet counts collectively explained 65% of the variation in positive public sentiment. These findings indicate that coordinated communication activities were associated with the concentration of positive narratives and higher engagement levels on platform X. This study contributes to research on digital political communication and data analytics by combining text mining, sentiment analysis, social network analysis, and statistical modeling to examine coordinated political communication activities. The findings also indicate the need for stronger digital literacy and monitoring approaches to identify coordinated digital propaganda activities on social media.

Keywords: Political Buzzer; Sentiment Analysis; Digital Propaganda; Data Analytics; Social Network Analysis.

1. Introduction

Political communication patterns in Indonesia have changed substantially with the rapid growth of social media (Fadillah & Azhar, 2026). Social networking platforms have become major spaces for shaping public opinion because they enable information to be disseminated rapidly, widely, and interactively. Among these platforms, X has emerged as an important digital communication channel for political discourse because of its real-time interaction and hashtag-driven communication structure (Aribowo, 2018). Buzzer activities are frequently used in digital politics to promote particular narratives and increase the visibility of political figures through repeated and coordinated information dissemination. This phenomenon became increasingly visible during the first 100 working days of President Prabowo Subianto's administration, particularly as several national survey institutions reported high levels of public satisfaction with government performance. According to Litbang Kompas, public satisfaction with the Prabowo administration reached 80.9%, while Indikator Politik Indonesia reported 79.3% (PT Indikator Politik Indonesia, 2025), and the Indonesian Survey Institute reported 81.4% during the same period (Nufus, 2025).

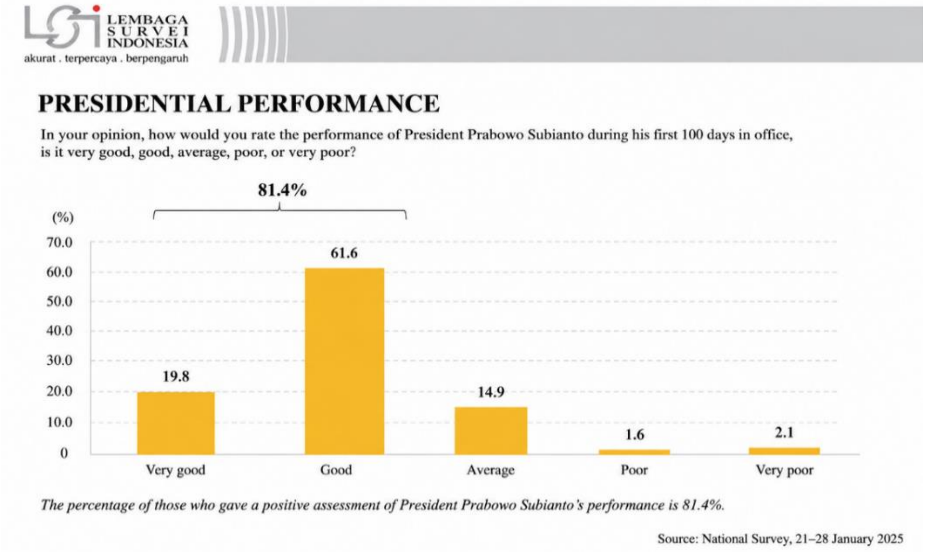

Figure 1. LSI Survey Result (Nufus, 2025)

Social media is used not only as a communication tool but also as a space for political actors and coordinated accounts to promote particular narratives and shape public discourse. Political buzzers may use reposts, hashtags, and engagement amplification to increase the visibility of specific political messages. Woolley and Howard (2017) explained that digital propaganda can employ coordinated communication through social media to influence public discourse. Furthermore, Stella *et al.* (2018) demonstrated that automated accounts can increase the exposure of political content and contribute to the spread of political information across online networks. These activities are relevant to the study of public sentiment because repeated and highly visible political messages may be associated with patterns of engagement and sentiment on social media. However, the presence of coordinated communication does not necessarily mean that positive or negative opinions expressed on social media are generated by buzzer activities. Public interest, political events, media coverage, and organic user interactions may also contribute to observed sentiment patterns.

Previous studies have investigated digital political communication, political buzzer activities, and public sentiment on social media. However, many studies have focused on political bot identification, digital propaganda, or social media behavior during election periods. Syahrohim *et al.* (2024) examined sentiment analysis following the 2024 presidential election, while Christhoper *et al.* (2026) analyzed public sentiment concerning the issue of President Joko Widodo's certificate authenticity. Adiyatma *et al.* (2024) examined public sentiment on platform X regarding the use of social assistance during the 2024 presidential election. These studies mainly focused on sentiment classification and specific political issues rather than examining the relationship between coordinated account activities and public sentiment during the early period of a presidential administration. Amanda *et al.* (2024) also examined sentiment on platform X, but the analysis did not combine sentiment analysis with social network analysis and statistical analysis to examine coordinated account activities and their relationship with public sentiment.

The existing literature therefore indicates a gap in the integrated analysis of coordinated political communication activities and public sentiment during the early period of government administration. In particular, limited research has examined the first 100 working days of President Prabowo Subianto's administration using a combination of text mining, sentiment analysis, social network analysis, and statistical analysis. Previous studies in Indonesia have also paid limited attention to the relationship between coordinated account activities and public sentiment on platform X, where political information can spread rapidly through reposts, hashtags, mentions, and interactions among accounts (Adib *et al.*, 2024). This study addresses this gap by applying a multidimensional analytical approach to examine the relationship between buzzer activities, digital communication network patterns, and public sentiment during the first 100 working days of the Prabowo administration.

For the purposes of this study, a political buzzer account is operationally classified based on behavioral indicators related to posting frequency, retweet activity, hashtag repetition, and account age. An account is classified as a political buzzer when it meets at least three of the following indicators: posting more than 50 posts per day, having a retweet-to-original-post ratio above 80%, having a hashtag repetition rate above 70% within a 24-hour period, and having an account creation date within six months of the observed political period. These indicators are used as operational criteria to identify accounts exhibiting intensive and repetitive patterns of political communication. The classification considers behavioral, temporal, and interaction patterns that have been examined in previous research on coordinated or automated social media activity (Ferrara *et al.*, 2016). However, these thresholds are treated as operational criteria for this study rather than universal standards for identifying political buzzer accounts. The identified accounts are therefore interpreted as accounts exhibiting buzzer-like behavioral patterns rather than definitive evidence of organizational affiliation or automated operation.

The novelty of this study lies in the integration of four analytical approaches, namely text mining, sentiment analysis, social network analysis, and statistical analysis, to examine coordinated account activities and public sentiment on platform X. Text mining is used to identify dominant narratives, sentiment analysis is used to classify the polarity of posts, social network analysis is used to examine interaction patterns among accounts, and statistical analysis is used to examine the relationship between account activity and public sentiment. Unlike previous studies that mainly focused on a single analytical method or electoral campaign contexts, this study specifically investigates digital political communication during the first 100 working days of President Prabowo Subianto's administration. This period represents an important stage of government performance evaluation, during which political narratives, public trust, and perceptions of government performance are actively discussed in digital spaces.

2. Related Work

The rapid evolution of social media platforms has transformed political communication and increased scholarly attention to digital propaganda, political buzzer activities, computational propaganda, sentiment analysis, and social network analysis. Recent studies have examined how coordinated digital communication networks affect the visibility, dissemination, and engagement of political information in online environments (Sinaga *et al.*, 2025). Howard *et al.* (2023) highlighted the growing role of artificial intelligence, recommendation algorithms, and coordinated networks in shaping public discourse across social media platforms. Pote (2024) further explained that contemporary computational propaganda involves not only automated bots but also coordinated human actors operating through digital networks. Similarly, Nip and Berthelier (2024) discussed the development of social media sentiment analysis beyond simple polarity classification by considering factors such as network relationships, temporal dynamics, and the dissemination of sentiment. These studies indicate that digital political communication involves interactions between content, users, and network structures rather than isolated communication activities.

In the Indonesian context, several studies have applied sentiment analysis and social network analysis to examine political discussions on social media. Muharram *et al.* (2024) combined sentiment analysis and social network analysis to investigate political conversations on platform X, demonstrating the usefulness of integrating textual and network-based approaches to understand online political behavior. Syahrohim *et al.* (2024) evaluated machine learning algorithms for sentiment analysis of public opinion following the 2024 presidential election. Christhoper *et al.* (2026) applied the Naïve Bayes Classifier to analyze public sentiment regarding the issue of President Joko Widodo's certificate authenticity using Indonesian-language posts. Adiyatma *et al.* (2024) also examined public sentiment on platform X concerning the use of social assistance during the 2024 presidential election. These studies demonstrate the growing use of machine learning and sentiment analysis to examine political discussions on Indonesian social media.

Despite these developments, several limitations remain. Muharram *et al.* (2024) combined sentiment analysis and social network analysis for political discussions on platform X, but the study focused primarily on interaction structures and sentiment polarity rather than statistically examining the relationship between coordinated account activity and public sentiment. Sidauruk and Herowati (2026) applied IndoBERT for political sentiment classification and reported high classification performance, but their analysis focused on text classification rather than coordinated communication patterns or political buzzer networks. Khairunnisa and

Siregar (2025) demonstrated the potential of combining sentiment analysis and social network analysis, although their research examined educational technology rather than political communication. These studies demonstrate the usefulness of individual analytical approaches and, in some cases, their combination, but they do not fully address the relationship between coordinated political account activity, network structures, and public sentiment in the context of an ongoing government administration.

Table 1. Comparison between Previous Studies and the Proposed Research

Study	Sentiment Analysis	Social Network Analysis	Statistical Analysis	Political Buzzer Analysis	Indonesian Context
(Muharram *et al.*, 2024)	✓	✓	✗	✗	✓
(Sidauruk & Herowati, 2026)	✓	✗	✗	✗	✓
(Howard *et al.*, 2023)	✗	✗	✗	✓	✗
This research	✓	✓	✓	✓	✓

The comparison indicates that previous studies have generally examined one or two analytical dimensions, such as sentiment classification, network analysis, or coordinated account detection. The combination of these approaches with statistical analysis remains less common, particularly in studies of political communication on platform X in Indonesia. The primary research gap therefore concerns the limited number of studies that examine the relationship between coordinated account activities and public sentiment using multiple analytical perspectives. Rather than treating sentiment, network structure, and account activity as separate phenomena, this study examines their relationships during the first 100 working days of President Prabowo Subianto's administration.

Previous research also provides methodological foundations for the analytical approaches used in this study. Text mining has been widely applied to extract information from large collections of social media data, while TF-IDF and Latent Dirichl*et al*location (LDA) have been used to identify important terms and topics in textual datasets (Nip & Berthelier, 2024). Sentiment analysis has been applied to classify political opinions into positive, negative, and neutral categories, including through machine learning algorithms such as Naïve Bayes (Syahrohim *et al.*, 2024; Christhoper *et al.*, 2026; Adiyatma *et al.*, 2024). Social network analysis has also been used to examine interaction patterns among social media users through retweets, mentions, and replies (Heryono *et al.*, 2024). These methodological developments provide a basis for selecting text mining, sentiment analysis, and network analysis in research on political communication.

However, the existing literature also indicates that each analytical approach captures a different dimension of social media activity. Text mining identifies the content and topics discussed by users, sentiment analysis describes the polarity of expressed opinions, and social network analysis identifies interaction structures among accounts. Statistical analysis can then be used to examine whether variations in account activity are associated with variations in public sentiment. Therefore, combining these approaches provides a more suitable basis for examining the relationship between coordinated account activities, communication network patterns, and public sentiment than relying on a single analytical method. This synthesis provides the basis for the methodological design of the present study, which combines text mining, sentiment analysis, social network analysis, and statistical analysis to examine political communication on platform X during the first 100 working days of the Prabowo administration.

3. Methodology

This study employed a quantitative approach based on social media data analytics to examine the relationship between coordinated account activities and public sentiment regarding President Prabowo Subianto's governmental performance on platform X during the first 100 working days of his administration. The study analyzed 10,000 public posts collected from platform X during the period from October 20, 2024, to January 29, 2025. The dataset was analyzed to identify textual patterns, sentiment distribution, account interaction structures, and statistical relationships between account activity and positive sentiment. The posts were selected using a stratified random sampling approach based on temporal distribution. The sampling procedure was used to distribute the selected posts across the observation period and to account for variations in the volume of political discussions over time. The final dataset contained the textual content of posts, posting timestamps, account identifiers, engagement metrics, and associated hashtags. These variables were used for text mining, sentiment analysis, social network analysis, and statistical analysis. Approximately 40% of the analyzed posts originated from December 2024, when discussions concerning the Free Nutritious Meal

Program (MBG) became prominent. Approximately 35% of the posts were collected during early January 2025, coinciding with public discussions concerning government performance satisfaction surveys conducted by Litbang Kompas and Indikator Politik Indonesia. This temporal distribution was retained in the analysis to capture variations in political discussions during periods of increased public attention to government policies and performance.

3.1 Data Collection

Data collection was conducted through the X API using the Tweepy library in Python. The search terms included "Prabowo," "Prabowo performance," "Free Nutritious Meal Program," "public satisfaction survey," and "corruption eradication." The primary hashtags included #PrabowoPresiden, #MBG, and #KabinetMerahPutih. The data collection process was conducted during the observation period from October 20, 2024, to January 29, 2025. The collected posts were compiled into a dataset containing textual content, posting timestamps, account identifiers, engagement metrics, and associated hashtags. Duplicate records, missing information, and inconsistent data formats were examined during the data-cleaning process before the data were used in the subsequent analyses.

3.2 Text Mining

Text mining was conducted to identify frequently occurring terms, relevant keywords, and major discussion topics in posts concerning the Prabowo administration. Word frequency analysis was used to identify commonly occurring terms and hashtags. Term Frequency–Inverse Document Frequency (TF-IDF) was applied to identify terms that were particularly relevant within the document collection, while Latent Dirichl *et al*location (LDA) was used to identify groups of words representing major discussion topics. The results of the text-mining analysis were used to describe the dominant narratives appearing in discussions concerning government performance, policy initiatives, and political issues during the observation period. These results were subsequently considered alongside the sentiment and social network analyses.

3.3 Sentiment Analysis

Sentiment analysis was conducted to classify posts concerning the governmental performance of President Prabowo Subianto into positive, negative, and neutral categories. The Naïve Bayes algorithm was used as the sentiment classification method because of its computational efficiency in text classification. For model development and evaluation, the sentiment dataset was divided into training and testing data using an 80:20 ratio. The training data were used to develop the sentiment classification model, while the testing data were reserved for evaluating the final model performance. Five-fold cross-validation was applied to the training data to evaluate the consistency of the classification model during model development. In each iteration, the training data were divided into five subsets, with four subsets used for training and one subset used for validation. The process was repeated five times so that each subset was used as the validation set once. Model performance was evaluated using accuracy, precision, recall, and F1-score.

3.4 Identification of Buzzer-Like Accounts

Accounts exhibiting intensive and repetitive political communication patterns were identified using the operational criteria defined in this study. Four behavioral indicators were considered: posting frequency, retweet-to-original-post ratio, hashtag repetition rate, and account age. An account was classified as a buzzer-like account when it met at least three of the following four criteria:

1) posting more than 50 posts per day.
2) having a retweet-to-original-post ratio above 80%.
3) having a hashtag repetition rate above 70% within a 24-hour period.
4) having an account creation date within six months of the observed political period.

These criteria were applied as operational indicators for identifying accounts with buzzer-like behavioral patterns in the dataset. The classification does not constitute definitive evidence that an account was operated by a political organization, coordinated group, or automated system. Instead, the classification identifies accounts whose observed behavioral characteristics meet the operational criteria established for this study.

3.5 Social Network Analysis

Social Network Analysis (SNA) was conducted using the NetworkX library to examine interaction structures among accounts involved in the dissemination of political content. The network was constructed using interactions represented by reposts, mentions, and replies. Each account was represented as a node, while interactions between accounts were represented as edges. Degree centrality was calculated to measure the connectivity of each account within the interaction network. Accounts classified as buzzer-like were then examined according to their positions and connections within the network. The SNA results were used to describe interaction patterns and identify accounts with relatively high connectivity within the observed network.

3.6 Statistical Analysis

Statistical analysis was conducted to examine the relationship between buzzer-related account activities and positive public sentiment. Pearson correlation was used to measure the direction and strength of linear relationships between the analyzed variables. Linear regression was subsequently applied to examine the association between account activity variables and variation in positive sentiment. The independent variables included posting frequency, hashtag quantity, and repost counts, while positive sentiment was used as the dependent variable. Statistical significance was evaluated using a significance level of 0.05. A p-value below 0.05 was considered statistically significant. The statistical analysis was used to assess associations between the variables and was not interpreted as evidence of a causal relationship.

3.7 Data Preprocessing and Exploratory Analysis

Before the primary analyses were conducted, the collected posts underwent data-cleaning and text-preprocessing procedures. Duplicate records, missing information, and inconsistent data formats were examined and addressed to ensure that the dataset was suitable for subsequent analysis. Text preprocessing included tokenization, case folding, stemming, stopword removal, and transformation of textual information into numerical representations using TF-IDF. These procedures were applied to standardize the textual data and prepare them for text mining and sentiment classification. Exploratory data analysis was then conducted to examine the characteristics and distribution of the dataset. Descriptive statistics and visualizations, including word clouds, histograms, line plots, and bar charts, were used to describe the temporal distribution of posts, frequently occurring terms, sentiment distribution, and account activity patterns.

3.8 Validation

Several procedures were applied to evaluate the reliability of the analytical results. The sentiment classification model was evaluated using five-fold cross-validation on the training data and subsequently assessed using the testing data. Accuracy, precision, recall, and F1-score were used to evaluate classification performance. The statistical analysis was evaluated using Pearson correlation and linear regression. Statistical significance was assessed using a significance level of 0.05. The results of the model evaluation and statistical analysis are presented in the Results section.

3.9 Research Stages

The research was conducted through a series of sequential stages, beginning with problem identification and literature review, followed by data collection, data cleaning, text preprocessing, exploratory data analysis, text mining, sentiment analysis, social network analysis, statistical analysis, validation, and interpretation of the results. The sequence of these research stages is presented in Figure 2.

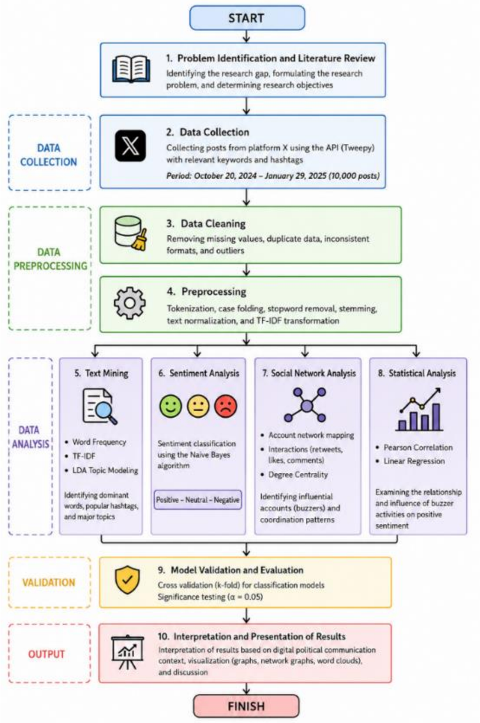

Figure 2. Research Stages

The research process began with problem identification and a literature review concerning digital political communication, social media propaganda, sentiment analysis, and political buzzer activities. The next stage involved collecting public posts through the X API using the Tweepy library. The collected data were then subjected to data cleaning to identify duplicate records, missing information, and inconsistent formats. Following data cleaning, text preprocessing was conducted through tokenization, case folding, stemming, stopword removal, and TF-IDF transformation. Exploratory data analysis was subsequently conducted to examine the characteristics of the dataset and identify initial patterns in political discussions and account activities. The next stage consisted of four analytical procedures. First, text mining was conducted using word frequency analysis, TF-IDF, and LDA to identify dominant terms and discussion topics. Second, sentiment analysis was conducted using the Naïve Bayes algorithm to classify posts into positive, negative, and neutral categories. Third, social network analysis was conducted using NetworkX to examine interaction structures and account connectivity. Fourth, statistical analysis was conducted using Pearson correlation and linear regression to examine the relationships between account activities and positive sentiment. The final stage involved validation and interpretation of the analytical results. Five-fold cross-validation was applied to the training data to evaluate the consistency of the sentiment classification model, while the testing data were used for final model evaluation. Statistical significance testing was conducted using a significance level of 0.05. The results from the text mining, sentiment analysis, social network analysis, and statistical analysis were then interpreted to describe the relationship between coordinated account activities, interaction patterns, and public sentiment during the first 100 working days of the Prabowo administration.

4. Result and Discussion

4.1 Results

The analysis was conducted on 10,000 public posts collected from platform X during the period from October 20, 2024, to January 29, 2025. The dataset was analyzed using text mining, sentiment analysis, social network analysis, and statistical analysis to examine political communication patterns, buzzer-like account activities, and their association with public sentiment regarding President Prabowo Subianto's governmental performance. The text mining results indicated that the dominant narratives concerned the Free Nutritious Meal Program (MBG), public satisfaction, and corruption eradication. Word frequency analysis showed that the terms "Prabowo," "MBG," "performance," "survey," and "satisfaction" occurred frequently in the collected posts. The hashtags #MBG and #PrabowoPresiden were also among the dominant hashtags during the observation period. These findings indicate that discussions concerning government performance were concentrated around government programs, public satisfaction, and policy-related issues (Figure 3).

Figure 3. Word Cloud of Dominant Narratives

The topic modeling results obtained using Latent Dirichl*et al*location showed that approximately 40% of the posts were associated with the Free Nutritious Meal Program, 25% concerned corruption eradication, and 20% concerned public satisfaction with the Prabowo administration. These three topics accounted for approximately 85% of the posts assigned to the major topics identified in the analysis, while the remaining 15% represented other topics with lower proportions. The distribution indicates that discussions concerning the MBG program, corruption eradication, and public satisfaction constituted the main thematic groups in the dataset. The concentration of discussions around these topics indicates that government programs, corruption eradication, and public satisfaction were prominent subjects during the observation period. However, thematic concentration alone does not establish that these narratives were generated or amplified through coordinated account activities. The observed concentration may also reflect genuine public interest, government announcements, media coverage, and other political events. Previous research has shown that political bots and coordinated digital activities can contribute to the amplification and dissemination of political content, particularly when multiple accounts repeatedly circulate related narratives (Stella *et al.*, 2018). Sentiment analysis showed that 62% of the posts, equivalent to 6,200 posts, were classified as positive, while 28%, or 2,800 posts, were classified as neutral, and 10%, or 1,000 posts, were classified as negative. The distribution indicates that positive sentiment was dominant within the analyzed posts during the observation period (Figure 4).

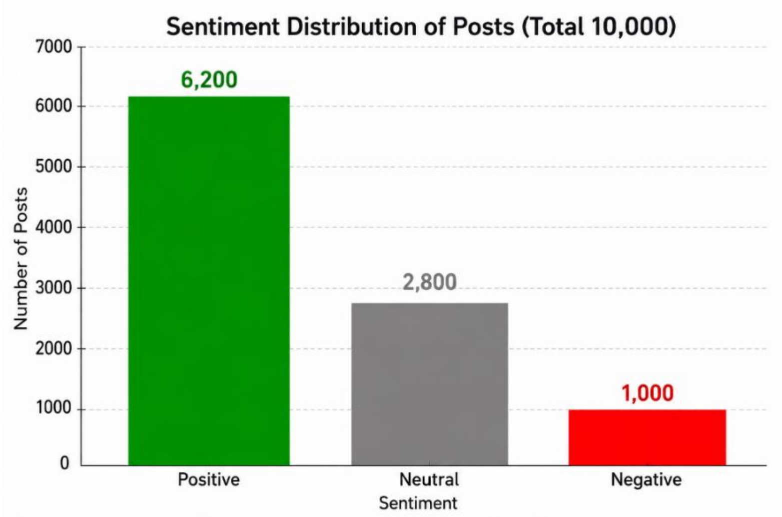

Figure 4. Sentiment Distribution of Posts

The temporal analysis showed that the proportion of positive sentiment increased from 55% in November 2024 to 70% in January 2025, with the highest reported level occurring between January 4 and January 10, 2025 (Figure 5). Negative sentiment remained below 15% during the reported observation period. The increase in positive sentiment occurred during a period of considerable public discussion concerning government performance and satisfaction surveys. However, the temporal coincidence between these events does not by itself establish that the survey publications or coordinated account activities caused the observed increase in positive sentiment.

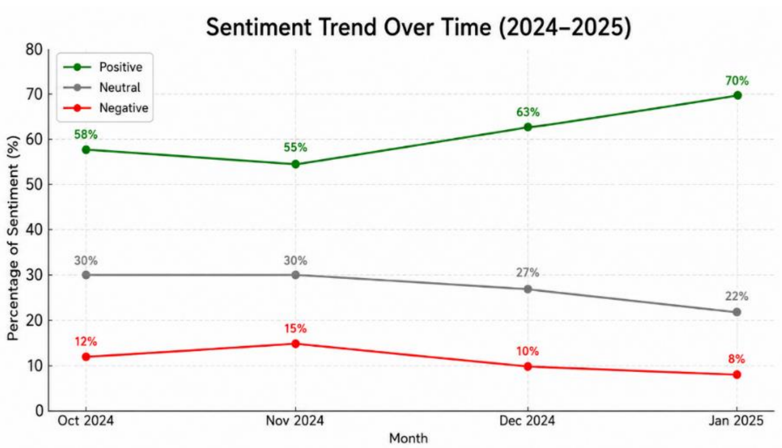

Figure 5. Sentiment Trend Based on Time (2024–2025)

Social Network Analysis revealed centralized interaction patterns involving several highly connected accounts. Degree centrality analysis identified 50 accounts with the highest degree-centrality values within the observed interaction network. In addition, 35 accounts repeatedly posted content containing #MBG and #PrabowoPresiden during the observation period. These accounts were examined as part of the group exhibiting relatively intensive political communication activity. The Louvain community detection analysis identified three major account communities within the interaction network (Figure 6).

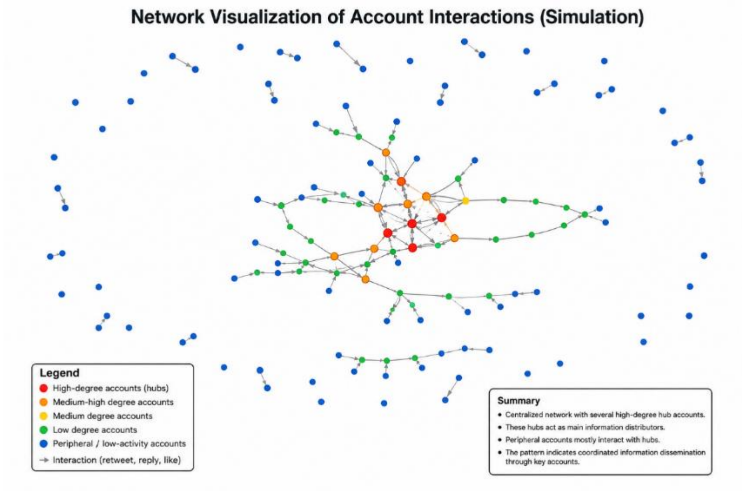

Figure 6. Network Graph of Account Interactions

Accounts with high degree centrality occupied relatively central positions within the observed interaction network and were connected to a larger number of other accounts. Such network positions can facilitate the dissemination of political content across connected users. Previous research has associated coordinated and centralized patterns of social media activity with computational propaganda and political automation (Ferrara *et al.*, 2016). However, high degree centrality alone does not establish that an account is a political buzzer or that its activity is automated. The analysis also showed a substantial difference in retweet activity between accounts classified as buzzer-like and other accounts. Buzzer-like accounts received approximately 500 retweets per post, compared with approximately 50 retweets per post for other accounts. These figures represent the average retweet count per post calculated for the respective account groups during the observation period. The difference indicates substantially higher engagement associated with the accounts classified as buzzer-like, although the result should be interpreted together with the statistical comparison between the two groups.

Pearson correlation analysis was conducted using daily aggregated observations across the observation period. For each day, buzzer-like posting frequency and the proportion of positive sentiment were calculated as paired observations. The analysis produced a positive correlation between daily buzzer-like posting activity and daily positive sentiment ($r = 0.78$, $p < 0.01$). This result indicates a strong positive temporal association between the two variables. The correlation should not, however, be interpreted as evidence that buzzer-like activity directly caused changes in public sentiment. The relationship was also examined specifically among posts containing the hashtag #MBG. The #MBG-specific analysis showed a positive association between buzzer-like account activity and positive sentiment. The result provides additional evidence that the relationship observed in the overall dataset was also present within discussions concerning the Free Nutritious Meal Program. The exact coefficient and significance level should be reported from the corresponding #MBG subset analysis.

Linear regression analysis was conducted using buzzer-like posting frequency, hashtag quantity, and retweet counts as independent variables and positive sentiment as the dependent variable. The three independent variables collectively explained approximately 65% of the variation in positive sentiment. Accordingly, the coefficient of determination for the reported model was $R^2 = 0.65$. The regression model was used to assess the extent to which the observed account activity variables were statistically associated with variation in positive sentiment. The regression coefficient for buzzer-like posting frequency was statistically significant and positive. The exact coefficient and p-value should be reported according to the regression output. The positive coefficient indicates that higher buzzer-like posting frequency was associated with a higher proportion of positive sentiment when the other variables in the model were considered. An independent-samples t-test was also conducted to compare retweet activity between buzzer-like accounts and other accounts. Buzzer-like accounts recorded approximately 500 retweets per post on average, compared with approximately 50 retweets per post for other accounts. The statistical test indicated a significant difference in retweet activity between the two groups. The exact t value, degrees of freedom, and p-value should be reported according to the statistical output.

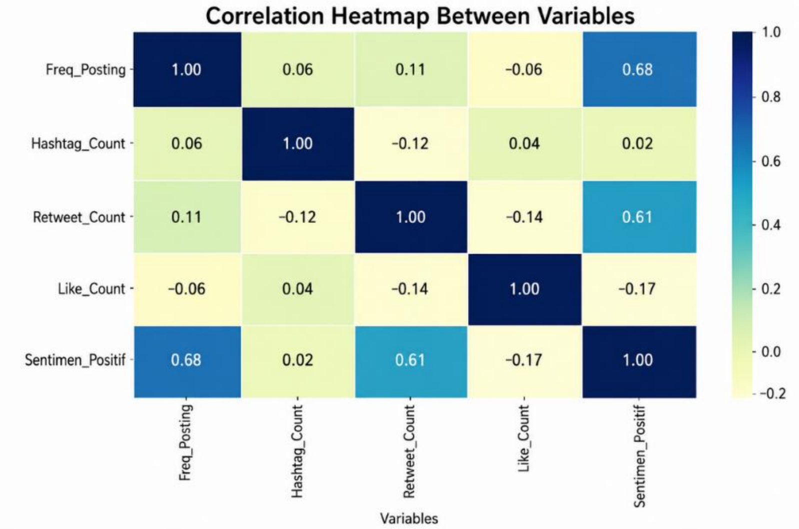

Figure 7. Correlation Heatmap of Buzzer-Like Activity Variables and Public Sentiment

The correlation and regression results indicate that higher levels of buzzer-like account activity were associated with higher levels of positive sentiment in the analyzed dataset. These findings provide evidence of a statistical association between communication activity and sentiment but do not establish a causal effect. Previous studies have similarly shown that automated and coordinated accounts can contribute to the amplification of political content and engagement within online networks (Bessi & Ferrara, 2016; Hagen *et al.*, 2022).

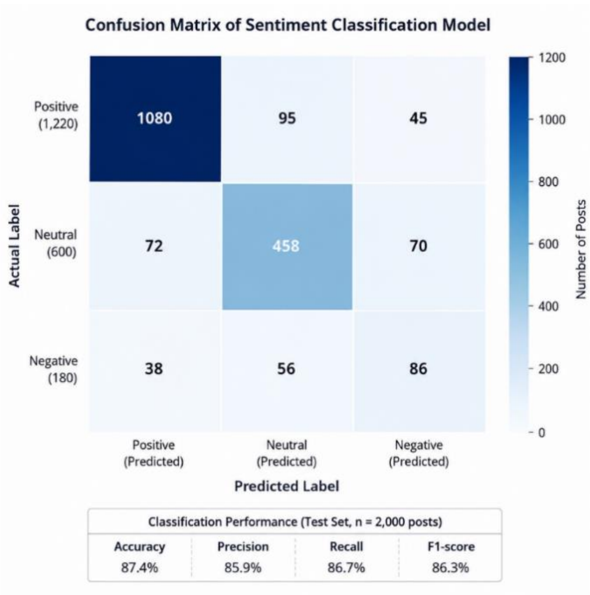

Figure 8. Confusion Matrix

The performance of the sentiment classification model was evaluated using the testing dataset. The confusion matrix showed that the Naïve Bayes classifier correctly classified the majority of posts across the three sentiment categories. The model achieved an accuracy of 87.4%, precision of 85.9%, recall of 86.7%, and F1-score of 86.3%. The reported precision, recall, and F1-score represent the aggregate evaluation of the three sentiment classes. The averaging method used in the classification report should be stated explicitly as macro-average, weighted-average, or another averaging method according to the model output. This information is necessary because the interpretation of the reported metrics depends on the averaging procedure. The classification results indicate that the Naïve Bayes model provided reasonably consistent performance in classifying sentiment within the analyzed dataset. Classification errors between neutral and negative sentiment may be related to contextual ambiguity, informal language, and implicit expressions commonly found in political discussions on social media.

4.2 Discussion

The results indicate that political discussions concerning the Prabowo administration on platform X were concentrated around several major topics, particularly the Free Nutritious Meal Program, corruption eradication, and public satisfaction. The three dominant topics represented approximately 85% of the posts assigned to the major topic groups identified through LDA, while the remaining 15% consisted of other topics with lower proportions. This distribution suggests that government-related issues dominated the observed political conversation during the study period. The dominance of positive sentiment and its increase in January 2025 also coincided with greater discussion of government performance and public satisfaction surveys. However, these results should not be interpreted as a direct measure of the overall perception of the Indonesian population because the dataset consisted of publicly available posts on platform X rather than responses from a probability-based population survey.

The Social Network Analysis showed that several accounts occupied relatively central positions within the observed interaction network. The 50 accounts with the highest degree-centrality values were located in more connected positions, while 35 accounts repeatedly posted content containing #MBG and #PrabowoPresiden. The Louvain analysis also identified three major communities, indicating that political communication within the observed network was not evenly distributed across all accounts. Some accounts were more connected and participated more frequently in disseminating selected political narratives. This pattern was also reflected in retweet activity: accounts classified as buzzer-like received approximately 500 retweets per post on average, compared with approximately 50 retweets per post among other accounts. Although this difference suggests substantially higher engagement among buzzer-like accounts, high engagement alone cannot establish that an account was coordinated, automated, or operated by a political organization.

The statistical findings further support the presence of an association between buzzer-like account activity and positive sentiment. Pearson correlation analysis showed a strong positive temporal association between buzzer-like posting frequency and positive sentiment, with $r = 0.78$ and $p < 0.01$. Because the analysis was based on daily aggregated observations, the coefficient represents co-variation between daily account activity and daily sentiment levels rather than a relationship between individual posts. The regression analysis also indicated that buzzer-like posting frequency, hashtag quantity, and retweet counts jointly explained approximately 65% of the variation in positive sentiment. This result suggests that the analyzed communication activity variables were associated with substantial variation in daily positive sentiment. Nevertheless, the finding should not be interpreted as evidence of a causal relationship because the study used observational social media data and did not experimentally manipulate account activity or control for all external factors that could affect sentiment.

The observed concentration of political narratives and interaction patterns has implications for digital political communication. Coordinated or highly repetitive dissemination can increase the visibility of particular topics and may affect which narratives receive greater attention within online networks. At the same time, the observed patterns may also result from legitimate political mobilization, active supporters, media attention, or other forms of organic participation. Therefore, the findings are better interpreted as evidence of buzzer-like behavioral patterns and their association with sentiment, rather than definitive evidence of organized political manipulation. This distinction is also important when interpreting social media engagement because metrics such as retweets do not necessarily represent independent expressions from individual users. When a relatively small group of highly active accounts generates substantial engagement, the visibility of a narrative may exceed what would be expected from ordinary individual participation.

The results should also be distinguished from the concept of an echo chamber. Although the network analysis identified centralized interaction patterns and several account communities, positive sentiment alone does not provide sufficient evidence to establish the existence of an echo chamber. Stronger evidence would require analysis of interaction homophily, cross-community communication, content similarity, and repeated exposure. Accordingly, the present findings are more appropriately interpreted as evidence of concentrated communication patterns rather than definitive evidence of an echo chamber.

These findings are consistent with broader research on computational propaganda and coordinated political communication. Studies in several political contexts have shown that political bots, algorithmically driven accounts, and coordinated social media behavior can contribute to the amplification of political messages, particularly when repeated content and dense network structures are involved [tambahkan referensi]. The Indonesian political communication environment also has specific characteristics, including active hashtag use, political influencers, online communities, informal language, and highly shareable political content. These characteristics may contribute to the rapid circulation of political narratives on platform X and provide contextual evidence concerning the relationship between account activity, network structure, and sentiment during the early period of the Prabowo administration.

From the perspective of industrial engineering and data analytics, the findings demonstrate the usefulness of combining text mining, machine learning, network analysis, and statistical modeling to examine complex social media data. Text mining identifies dominant topics, sentiment analysis measures the polarity of posts, network analysis describes interaction structures, and statistical analysis quantifies relationships among the observed variables. Combining these approaches provides a broader description of political communication patterns than relying on a single analytical method. The findings also suggest potential applications for digital monitoring systems that combine behavioral indicators, network structures, content similarity, and engagement patterns to identify accounts exhibiting coordinated or highly repetitive activity. However, behavioral similarity does not necessarily establish malicious intent, organizational affiliation, or automated operation. Automated detection should therefore be complemented by contextual assessment and human review before an account is characterized as part of a coordinated political operation.

5. Conclusion and Recommendations

This study found a significant positive association between buzzer-like political communication patterns and positive sentiment on platform X regarding President Prabowo Subianto's governmental performance during the observed early period of his administration. Based on the analysis of 10,000 public posts, the dominant discussion topics were the Free Nutritious Meal Program (MBG), public satisfaction, and corruption eradication. The concentration of these topics indicates that political communication on platform X was characterized by recurring narratives and repeated patterns of information dissemination. Sentiment analysis further showed that 62% of the analyzed posts were classified as positive, while 28% were neutral and 10% were negative. The increase in positive sentiment during the period when national public satisfaction survey results were published suggests that sentiment dynamics on platform X coincided with periods of increased political attention. However, these findings should not be treated as a direct measure of the views of the Indonesian population as a whole because the dataset consisted of publicly available social-media posts rather than probability-based survey responses.

The social network analysis identified interaction patterns among accounts exhibiting buzzer-like behavioral characteristics. Accounts with high degree centrality occupied relatively central positions in the interaction network and were associated with the dissemination of political content. Repetitive hashtag usage, frequent posting, and high levels of repost activity indicated intensive and repetitive communication patterns, although these characteristics do not by themselves establish that the accounts were operated by a political organization or were fully automated. The statistical analysis also showed a strong positive relationship between daily buzzer-related posting activity and the proportion of positive sentiment, with a Pearson correlation coefficient of $r = 0.78$ ($p < 0.01$). Because this analysis used daily aggregated observations, the result represents temporal co-variation between daily account activity and daily sentiment levels rather than a relationship at the individual-post level. The linear regression model further indicated that posting frequency, hashtag quantity, and repost counts collectively explained approximately 65% of the variation in positive sentiment ($R^2 = 0.65$). These findings should therefore be interpreted as evidence of association, not as proof that buzzer activities directly caused changes in public opinion.

This study contributes to research on data analytics for digital political communication by combining text mining, sentiment analysis, social network analysis, and statistical analysis. This integrated approach allows political communication to be examined across several dimensions, including dominant topics, sentiment distribution, interaction structures, and statistical relationships between account activity and sentiment. Within industrial engineering and data analytics research, the approach is relevant for analyzing complex socio-technical systems in which user behavior, information dissemination, and network interactions occur simultaneously.

The findings also have practical implications for digital literacy and social-media monitoring. Social-media users need stronger critical awareness to evaluate political information and recognize repetitive or potentially coordinated communication patterns. Social-media platforms and relevant institutions may also consider monitoring mechanisms based on account behavior, network structures, and content patterns to identify potentially coordinated activities. Such mechanisms should be implemented carefully because high posting frequency, repetitive hashtags, or central network positions alone do not establish that an account is a political buzzer or that its content is inauthentic. The analysis was limited to publicly available posts on platform X and therefore does not represent political communication across other social-media platforms. The dataset consisted of Indonesian-language political posts collected using predefined keywords and hashtags, which may have excluded relevant discussions using different terminology. The identification of buzzer-like accounts was based on predefined behavioral indicators and network characteristics rather than verified organizational affiliation or a dedicated automated classification model. In addition, the statistical analysis examined associations between account activity and sentiment and cannot establish causal effects. The observation period was also limited to the early period of the Prabowo administration, so the findings may not represent longer-term changes in political communication patterns.

Future research should expand the dataset to other platforms, such as Instagram, TikTok, and Threads, to examine whether similar patterns occur across different social-media environments. Further studies may also employ more advanced machine-learning or graph-based methods to improve the identification of coordinated account behavior. Longitudinal analysis covering a longer period could be used to examine whether the relationship between coordinated communication activity and public sentiment remains stable over time. Future research may also investigate the social and behavioral implications of repeated political information exposure rather than focusing only on statistical relationships between digital activity and sentiment.

Acknowledgement

The authors would like to express their gratitude to Department of Industrial Engineering University of Mataram, who have provided support for this research. AI assisted language editing tools were used exclusively to improve grammar, readability, and language quality. All research activities, data collection, data analysis, interpretation of findings, and final manuscript preparation were conducted and verified by the authors.

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