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Understanding Public Perception Made Easy: A Sentiment Analysis of Public Transportation Services

Tutik Rachmawati[1], Haris Kahfi Nugraha[2]
[1] Public Administration Study Program, Universitas Katolik Parahyangan, Indonesia.
(corresponding author: tutikr@unpar.ac.id)
[2] Public Administration Study Program, Universitas Katolik Parahyangan, Indonesia.

Abstract

Public policy evaluations are often constrained by traditional methods that require significant time and resources, limiting their timeliness and impact. This research explores the use of X (formerly Twitter) sentiment analysis to evaluate public perceptions of TransJakarta services, addressing the shortcomings of conventional survey-based approaches. The study contributes to academic literature on big data in public administration and offers policymakers a faster and more inclusive method of capturing citizen perspectives. Using X data collected from September 2023 to May 2024, sentiment analysis was conducted using VADER and TextBlob, supported by complementary techniques including word frequency analysis, word clouds, and comparative analysis. The findings reveal that public sentiment fluctuates in response to service disruptions. Notable discrepancies between the VADER and TextBlob classifications indicate the value and necessity of manual validation. In contrast to earlier studies that employed complex models less accessible to practitioners, this study presents a simplified yet robust approach to big-data-driven evaluation, making sentiment analysis more practical for policy monitoring and improvement.

Keywords:
sentiment analysis; public perception; TransJakarta; public transportation; social media

Introduction

Public sentiment is increasingly recognised as a crucial indicator for evaluating the effectiveness of public services, particularly within the transportation sector. While traditional surveys and questionnaires offer only a limited scope, the rise of social media provides a broader and more timely means of understanding public opinion. This study positions itself within this shift, focusing on public transportation as a sector where real-time sentiment can critically inform policy decisions. Sentiment analysis, which involves extracting subjective information from text data, has become a vital tool for gauging public opinion on various issues (Geusan Akbar, 2021; Nursinggah, 2024; Saputra & Hasan, 2024), including public transportation systems. Historically, this analysis relied on traditional methods like surveys and questionnaires, which are static, offer a limited scope, and often fail to capture real-time public sentiment (Liu, 2015; Pang, 2008). These methods typically represent the views of a small, often self-selected group, which can lead to biased conclusions. The rise of big data and social media has created new opportunities to collect and analyse public sentiment more comprehensively, offering deeper and more immediate insights.

As Indonesia's capital and most densely populated province, Jakarta has long grappled with severe traffic congestion that affects the daily lives of millions. Live traffic data from TomTom (*https://www.tomtom.com/traffic-index/jakarta-traffic/)* shows that in 2023, Jakarta ranked 30th worst in the world for congestion. This situation necessitates smarter mobility solutions. The Bus Rapid Transit (BRT) service

TransJakarta, as part of the metropolis's public transportation system, has been developed to alleviate traffic congestion by providing a reliable alternative to private vehicles (Kumar, 2019). As such, public perception of TransJakarta's effectiveness is crucial as it directly influences ridership and the initiative's overall success. However, understanding public sentiment through traditional methods often provides an incomplete picture, as they typically exclude the perspectives of non-users (Boontarig, 2018; Bahri, 2022). This limitation necessitates more advanced analytical approaches to capture the full spectrum of public opinion.

Recent surveys suggest a high level of satisfaction with public transportation among Jakarta residents; for instance, 75.1% of respondents in a 2023 study by Litbang Kompas reported comfort in using the available modes. While informative, such surveys focus on existing users and overlook the perspectives of non-users. This gap shows how complementing survey data with social media analysis can be useful to capture a wider range of opinions.

As the Litbang Kompas survey on TransJakarta's service quality focused solely on the experiences of existing users, it captures only the perspectives of those already using the service, potentially leading to biased results. By excluding non-users who may have valid reasons for not utilising the service, such research fails to provide a comprehensive view of overall public perception. In contrast, our study adopts a different point of view by leveraging big data to capture a wider spectrum of public opinion about the services by including the voices of both users and non-users (Dokshin, 2022).

Traditionally, sentiment analysis for public services like TransJakarta has relied on questionnaires and structured interviews, which are inherently limited in both scope and real-time applicability (Cambria, 2017; Li, 2019; Chen, 2023). Such methods are often constrained by demographic reach and the subjective nature of self-reported data, which can lead to skewed results (Esuli, 2006). In contrast, machine learning algorithms applied to large datasets, such as those from X, provide a powerful alternative (Qureshi, 2024; Ilias, 2024; Kim, 2020) as these algorithms can process vast amounts of unstructured data to offer more dynamic insights reflective of broader public sentiment. This shift from conventional to data-driven techniques marks a significant step forward in public opinion studies (Bhardwaj, 2022; Hassan, 2018).

Previous research on TransJakarta has shown the value of these techniques. Rachman (2020) employed sentiment analysis alongside

Figure 1. Commuter Responses to the Quality of Public Transportation in Jakarta in 2023
Source: Litbang Kompas/AYP/IWN

the Latent Dirichlet Allocation (LDA) method to examine public opinion on the BRT service. Similarly, Nurthohari (2022) conducted an equivalent study using a support vector machine, and Meilani (2024) employed the Naive Bayes method for the same purpose. While these studies successfully derived meaningful insights from public sentiment, their technically complex nature makes them difficult for public sector practitioners to imitate. This study intends to bridge the gap by describing an approach to sentiment analysis that is designed to be more accessible and easily applicable within the public sector.

This work has a methodological novelty through its big data gathering process and analytical framework. It utilises machine learning to evaluate sentiment analysis tools for retrieving public opinion, using X as its main source of information. As a social media platform, X provides a steady stream of raw, real-time public opinion from both users and non-users alike, serving as a rich qualitative source (Pak & Paroubek, 2010; Kusuma, 2019). Unlike static surveys, machine learning-based sentiment analysis can track and measure fluctuations in public opinion as they happen, offering policymakers more contemporaneous and contextually relevant feedback (Tumasjan, 2011; Hossin, 2023). By using machine learning and big data technology, this research provides a broader and more accurate reflection of public sentiment regarding TransJakarta than traditional methods would allow (Feldman, 2013; Muhammad, 2020).

In brief, the study aims to address the inadequacies of traditional public opinion analysis tools by employing machine learning models to process vast quantities of posts on a social media platform. This approach makes it feasible to determine the overall public attitude towards TransJakarta's services by incorporating both user and non-user perspectives. In doing so, this study contributes to the growing body of public transport sentiment analysis literature and offers actionable insights that can inform the future development of TransJakarta services (Sharda, 2020; Liu, 2012). This marks a new era of public opinion measurement, characterised by more informative and up-to-date data that has the potential to immediately influence public transport policy.

Literature Review

Big data refers to vast and complex datasets that are difficult to process using conventional data-handling applications. These datasets are traditionally characterised by the “three Vs”: volume (the amount of data), variety (the numerous types of data), and velocity (the speed of data generation and processing). Laney (2001) and Anuraddha (2015) later introduced two further ‘V’ attributes: veracity and value. As a public sector asset, big data has the potential, if harnessed wisely, to greatly enhance decision-making, operational efficiency, and service delivery (Chen, 2014). Public sector organisations can benefit from drawing useful inferences through the analysis of such data, allowing for better resource allocation and effective responses to public demands (Zhang, 2018).

The impact of big data is particularly prominent in public services such as transportation. Public institutions are increasingly using big data to improve service delivery and make more informed decisions based on patterns identified within extensive datasets (Chahar, 2023). Public transportation systems, including services like TransJakarta, are adopting data-driven interventions to optimise routes, improve fleet management, and enhance customer satisfaction (Ma et al., 2019). These improvements are made possible by integrating real-time traffic flow data, analysing commuter patronage patterns, and applying operational analytics in order to make transportation services more efficient and better aligned with public needs (Schintler, 2014).

Machine learning helps public sector agencies to analyse complex public opinion, such as through sentiment analysis, by leveraging large-scale datasets. The natural language processing technique of sentiment analysis allows agencies to process vast quantities of textual data, identifying and labelling opinions and emotions. This approach can be applied to service feedback for systems like TransJakarta, where public sentiment expressed on social media can be monitored in real time to track evolving opinions (Cambria, 2017). Public transportation authorities can use machine learning to promptly identify areas of concern, streamline services, and enhance user satisfaction (Hu, 2019).

Sentiment analysis is a computational method used to detect and classify emotions within text data, typically categorising them as positive, negative, or neutral (Liu, 2012; Mao, 2024; Bordoloi, 2023). It has been widely employed to analyse unstructured data such as social media posts, customer feedback, and general public commentary to extract meaningful insights into collective sentiment (Umunyana, 2024). Core attributes of sentiment analysis include its ability to handle text data at an enormous scale, its use of machine learning algorithms to detect patterns, and its applicability across diverse sectors, from marketing to public administration (Pang, 2008; Islam, 2024). Public transportation services like TransJakarta can greatly benefit from this method, as public sentiment plays a significant role in guiding service improvements (Feldman, 2013).

While there has been extensive research on applying sentiment analysis in public services (Sabilla & Hartanto, 2024), such studies are often difficult for government practitioners to replicate, hindering the broader adoption of these techniques (Sharma, 2023). This study offers a distinct perspective by focusing specifically on a localised BRT service, TransJakarta, providing a practical learning model for government workers seeking to implement sentiment analysis. Whereas other research examined sentiment analysis broadly across diverse sectors, few have focused on urban transport sentiment trends, particularly within a complex urban sprawl like Jakarta (Saputra I. , 2022). This work breaks new ground by incorporating everyday social commentary about TransJakarta, yielding more accurate insights into public perception and potential service improvements. It extends beyond the pioneering work of researchers such as Dolicanin and Kajan (2014).

Despite the advantages brought by machine learning to sentiment analysis, there remain significant challenges, such as its inability to fully grasp the complexities of human language, such as sarcasm, humour, or culturally specific references (Jurafsky, 2021). This limitation shows the necessity for human intervention, as practitioners must cross-check machine-generated outputs to ensure accuracy and relevance. Without this human validation, the risk of misclassification and misinformation increases substantially (Gillespie, 2021). For the most reliable sentiment analysis of public services, machine learning and human intelligence must work in complement.

Methods

This research focused on sentiment analysis, a branch of Natural Language Processing (NLP) that involves processing textual data to identify and extract subjective sentiment. NLP is a field of artificial intelligence that enables computers to understand, interpret, and generate human language (Jurafsky, 2020). One of its most significant applications, as used in this study, is managing large volumes of text to detect and classify feelings or opinions that are typically categorised as positive, negative, or neutral. However, a considerable challenge arises when applying NLP to non-English languages, such as Indonesian. Unlike English, which benefits from a wide range of powerful pre-trained models and lexicons, Indonesian lacks similarly developed resources, making accurate sentiment analysis more difficult (Suryani et al., 2021). This language gap demands additional customisation and tailored modelling to achieve reliable results when working with non-English data (Tarecha, 2022).

The big data used in this research were collected from the social media platform X (formerly Twitter) using a keyword-based method. As one of the largest social networks, X provides a vast database of publicly shared opinions, becoming a valuable resource for studying public sentiment on various issues (Nasrullah, 2023; Rachman, 2020; Puluhulawa & Rajiyem, 2022). Data from users discussing specific topics were identified and compiled into a dataset using relevant keywords. Posts containing these keywords were extracted over a defined period using X's API. According to the *Digital 2023* report by We Are Social Indonesia, 60.2% of Indonesian users are active users of X, confirming the platform's suitability for capturing public mood in this study.

Machine learning forms the core of this research by automating the process of sentiment classification. Specifically, supervised learning models were employed to categorise X posts into predefined sentiment classes (Bishop, 2016). These models are trained on labelled datasets to recognise patterns and features associated with positive, negative, or neutral sentiment. Once trained, the system can predict sentiment in new data, allowing the analysis to be scaled to thousands of posts without human intervention. This approach is not without its challenges; the accuracy of the model is highly dependent on the quality and representativeness of the training data.

The research methodology follows a structured process of scientific data collection, application of machine learning algorithms for sentiment classification, followed by subsequent verification and analysis. Data collection begins with the extraction of posts from X using keywords relevant to the subject. These posts then undergo pre-processing, which includes tokenisation, stop word removal, and language normalisation to prepare the text for analysis. The pre-processed data is then input into the machine learning algorithms, which predict the sentiment of each

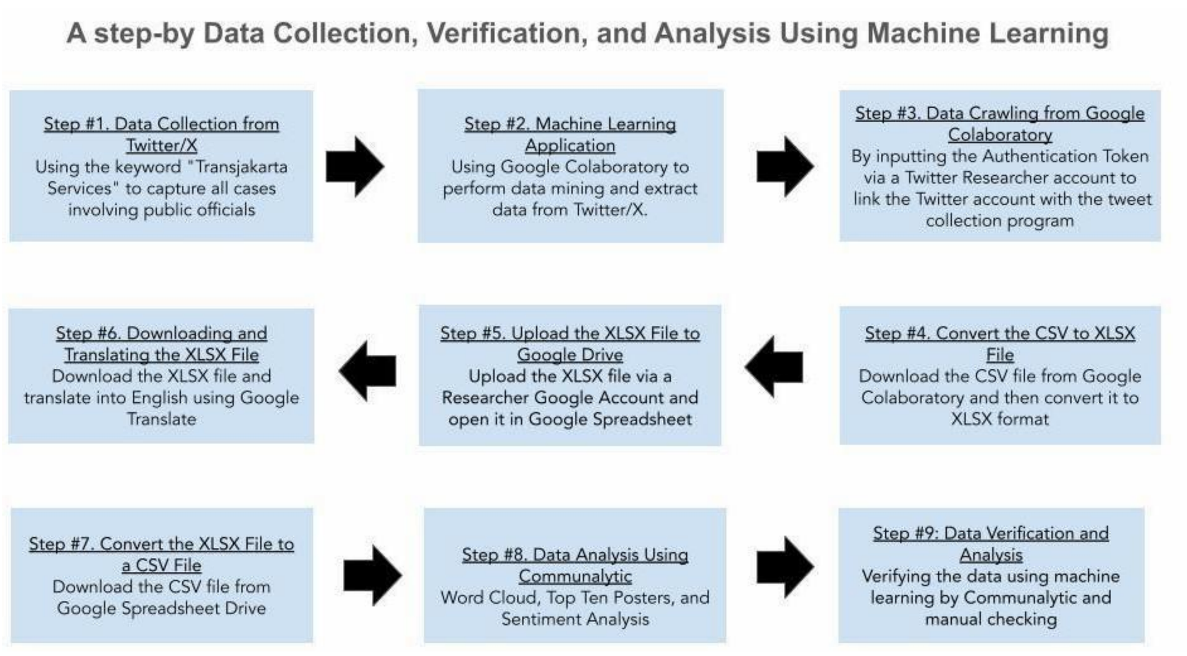


Figure 2. Steps in Sentiment Analysis
Source: Authors

post based on patterns learned during training. Finally, the predicted sentiments are evaluated to identify trends in public opinion and the overall nature of discussion surrounding the chosen topic (Manning, 2008; Sainger, 2021; Saraf, 2024).

A key area of this research is the interaction between post-truth dynamics and big data on social media (Overton & Kleinschmit, 2022). Hartono (2018) defines post-truth as a situation in which appeals to objective fact hold less influence over public opinion than appeals to emotion and personal belief. As an emotionally driven opinion platform, X can amplify the effect of misinformation, making sentiment analysis a useful yet imperfect tool (Huh, 2024). On platforms where users often share emotionally charged opinions, verifying the genuineness of expressed sentiments becomes increasingly challenging. For this reason, this research considers sentiment analysis in two ways: as an instrument for capturing public opinion, and as a means of measuring the influence of post-truth dynamics in the construction of that opinion.

Manual verification is necessary due to the inherent issues with social media big data, particularly its susceptibility to misinformation (Eng, 2021). To validate the authenticity of the collected data, this research uses Communalytic, a data validation software that enables researchers to verify social media data (Gruzd & Mai, 2024). Communalytic offers functionalities such as Cohen's Kappa and customisable VADER sentiment analysis, allowing for cross-validation of the sentiment scores generated by machine learning. For instance, Cohen's Kappa measures the reliability of agreement between different sentiment categorisation methods, helping to validate computational results against human interpretation. This type of validation is essential to filter out outliers such as bot-generated posts and to quantify the reliability of user-generated data.

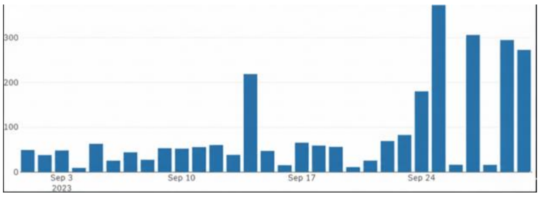
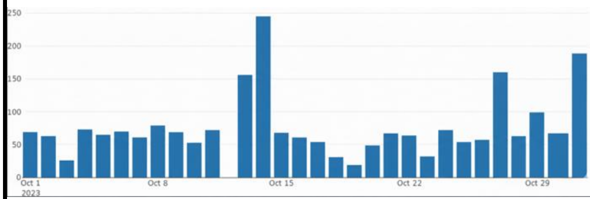
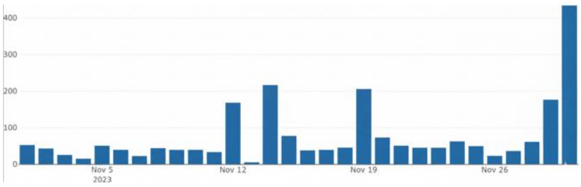
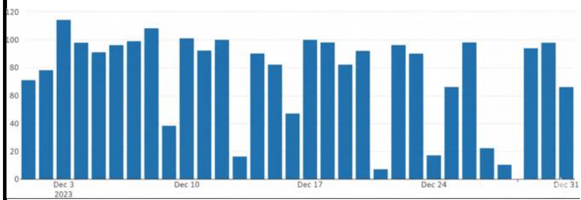
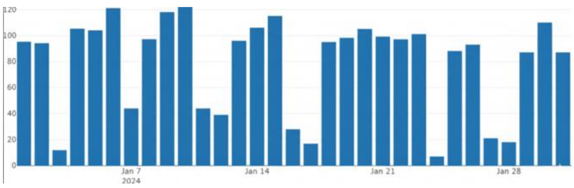
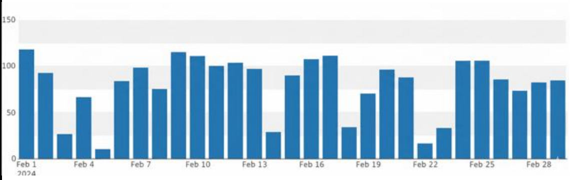
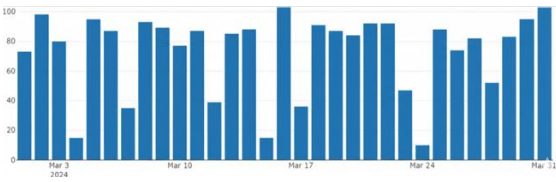
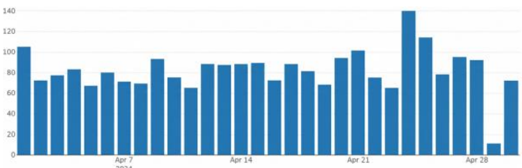
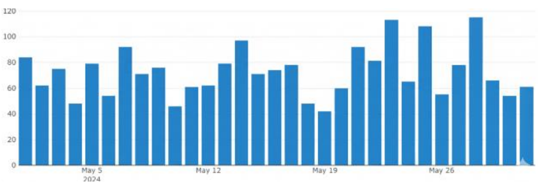
One of the major challenges in using social media data is its inherent lack of reliability. This research acknowledges that such data can be biased, manipulated, or inaccurate, which may compromise the results of sentiment analysis (Pasla, 2023). Consequently, although machine learning provides a scalable means of processing large datasets, human authentication is used to double-check the results (Gardner, 2021). This manual verification, facilitated by Communalytic, involves reviewing random samples of classified data to ensure the sentiments detected by the machine learning models accurately reflect genuine human expression.

Results

Following the methodological flow outlined in Figure 2, public sector practitioners can apply this process to data collected from X. This section presents the results of each stage. The study uses X data related to TransJakarta services, collected from September 2023 to May 2024. The analysis examines trends in posts per day, word cloud visualisations, top contributors, and sentiment analysis. This approach allows for a comprehensive understanding of public discourse surrounding the TransJakarta bus system, including key topics, sentiment trends, and the most engaged users. Over this period, fluctuations in post volume, engagement patterns, and specific content trends were observed. The results illustrate how users interacted with the system, offering valuable insights into public opinions and feedback.

The number of posts per day varied significantly across different months, showing bursts of activity followed by quieter periods. For example, in September 2023, a notable spike occurred between 23 and 30 September, with the highest number being 373 posts recorded on the 25th. The lowest activity was observed on the 4th, with only nine posts. This pattern continued in subsequent months, where

Table 1.
Posts Per Day

 September 2023	 October 2023
 November 2023	 December 2023
 January 2024	 February 2024
 March 2024	 April 2024
 May 2024	

Source: Communalytic

peaks on specific dates likely corresponded to significant events or public announcements. In October 2023, the highest volume of posts occurred on the 14th with 245 mentions, while the lowest was recorded on the 19th, with only 19 posts. November 2023 followed a similar pattern, peaking at 434 posts on the 30th and dropping to just 15 posts on the 4th.

Moving into the new year, January 2024 maintained a consistent level of activity, reaching a peak of 122 posts on the 10th. February 2024 also showed varied engagement, with the highest number of 168 posts occurring on the 7th.

The fluctuations suggest that user activity was largely event-driven, influenced by news related to service changes or disruptions. The analysis of daily posts revealed that public discussions surged in response to particular events, while periods of stability or fewer incidents resulted in decreased posting. These insights are valuable for public sector practitioners, especially those involved in public service delivery, in identifying the causes of service issues and developing targeted improvement measures.

The word cloud visualisations provided insight into the most frequently used terms within the tweets, revealing the dominant topics of public conversation. In September 2023, the most common words included "bus", "stop", "route", "TransJakarta", and "please". This suggests that discussions largely revolved around practical transportation matters such as routes and bus stops, with users often making requests or seeking information. Other prominent words like "time", "ask", and "thank" indicate a combination of inquiries about bus schedules and expressions of gratitude, likely in response to assistance received.

By October 2023, the focus had shifted. The most frequent words included "service", "customers", and "improve", showing a theme centred on customer service and feedback. In November 2023, terms such as "minutes", "waiting", and "operates" came to the fore, suggesting public discussion around bus schedules, waiting times, and operational issues. This evolution in the word clouds indicates how the nature of public discourse changes over time, showing concerns from practical navigation issues to broader themes of service quality and operational performance.

The top ten posters on X were identified on a monthly basis to determine the most active contributors in online discussions about TransJakarta. In September 2023, the busiest account was @Habib2611234979, who contributed 46 posts, representing 25.7% of the total. This was closely followed by the official TransJakarta account on X (@PT_TransJakarta) with 42 posts, accounting for 23.5% of the total. This pattern of the official account being among the most active users was observed throughout the entire study period. For example, in October and November of 2023, @PT_TransJakarta subsequently contributed 464 and 133 posts, representing 78.1% and 45.2% of all updates, showing active effort by the official account to engage in online discourse.

Discussion

Analysis of social media posts about TransJakarta between 2023 and 2024 shows both the intensity of public debate and the diversity of sentiments expressed. By applying VADER and TextBlob, this study captures trends in public engagement, sentiment, and user activity, offering valuable insights into how citizens experience and discuss the service.

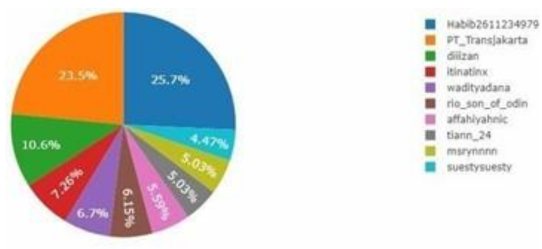
Sentiment analysis reveals the overall public sentiment variation towards TransJakarta, with discussions frequently focusing on punctuality, service announcements, or broader policymaking. These largely align with actual service disruptions or improvements, reflecting how public mood responds to operational performance. This finding supports earlier work demonstrating the significant

Table 2.
Word Cloud Visualisations

 September 2023	 October 2023
 November 2023	 December 2023
 January 2024	 February 2024
 March 2024	 April 2024
 May 2024	

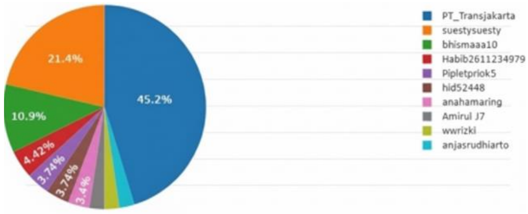
Source: Communalytic

Table 3.
Top Ten Posters

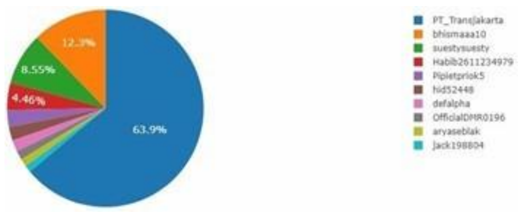


September 2023

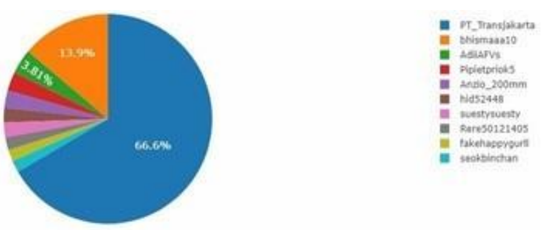
October 2023



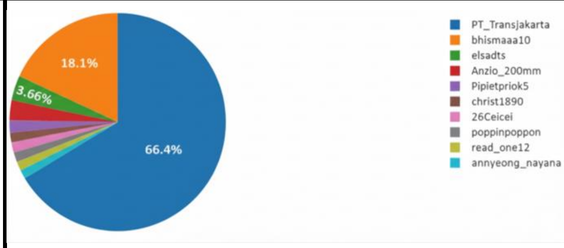
November 2023



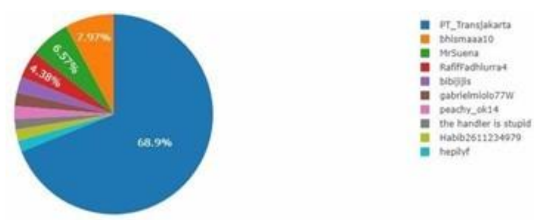
December 2023



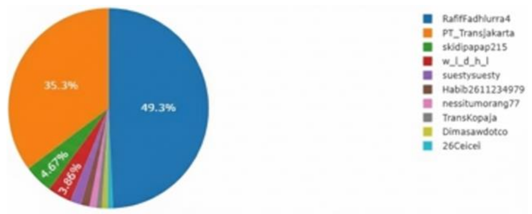
January 2024



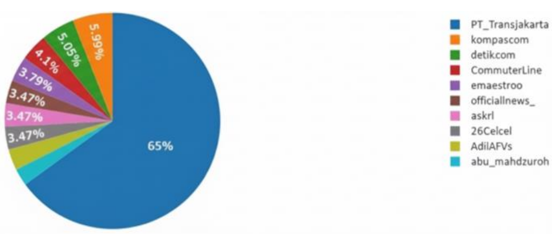
February 2024



March 2024



April 2024



May 2024

Source: Communalytic

Table 4.
Monthly Sentiment Distribution (VADER vs TextBlob), September 2023–May 2024

Results

Based on the analysis of **2280** out of 2667 posts, the results are as follows:

	# of Posts	Negative Sentiment [-1..-0.05]	Neutral Sentiment (-0.05..0.05)	Positive Sentiment [0.05..1]
VADER (English/EN)	2278	544 (23.88%)	774 (33.98%)	960 (42.14%)
TextBlob (English/EN)	2278	333 (14.62%)	1143 (50.18%)	802 (35.21%)

September 2023

Results

Based on the analysis of **2090** out of 2333 posts, the results are as follows:

	# of Posts	Negative Sentiment [-1..-0.05]	Neutral Sentiment (-0.05..0.05)	Positive Sentiment [0.05..1]
VADER (English/EN)	2086	468 (22.44%)	650 (31.16%)	968 (46.40%)
TextBlob (English/EN)	2086	366 (17.55%)	905 (43.38%)	815 (39.07%)
TextBlob (French/FR)	1	0 (0.00%)	1 (100.00%)	0 (0.00%)
TextBlob (German/DE)	3	0 (0.00%)	3 (100.00%)	0 (0.00%)

October 2023

Results

Based on the analysis of **1864** out of 2250 posts, the results are as follows:

	# of Posts	Negative Sentiment [-1..-0.05]	Neutral Sentiment (-0.05..0.05)	Positive Sentiment [0.05..1]
VADER (English/EN)	1864	495 (26.56%)	527 (28.27%)	842 (45.17%)
TextBlob (English/EN)	1864	336 (18.03%)	841 (45.12%)	687 (36.86%)

November 2023

Results

Based on the analysis of **2041** out of 2357 posts, the results are as follows:

	# of Posts	Negative Sentiment [-1..-0.05]	Neutral Sentiment (-0.05..0.05)	Positive Sentiment [0.05..1]
VADER (English/EN)	2040	416 (20.39%)	691 (33.87%)	933 (45.74%)
TextBlob (English/EN)	2040	363 (17.79%)	943 (46.23%)	734 (35.98%)
TextBlob (French/FR)	1	0 (0.00%)	1 (100.00%)	0 (0.00%)

December 2023

Results

Based on the analysis of **2148** out of 2463 posts, the results are as follows:

	# of Posts	Negative Sentiment [-1..-0.05]	Neutral Sentiment (-0.05..0.05)	Positive Sentiment [0.05..1]
VADER (English/EN)	2147	429 (19.98%)	694 (32.32%)	1024 (47.69%)
TextBlob (English/EN)	2147	368 (17.14%)	982 (45.74%)	797 (37.12%)
TextBlob (German/DE)	1	0 (0.00%)	1 (100.00%)	0 (0.00%)

January 2024

Results

Based on the analysis of **2145** out of 2452 posts, the results are as follows:

	# of Posts	Negative Sentiment [-1..-0.05]	Neutral Sentiment (-0.05..0.05)	Positive Sentiment [0.05..1]
VADER (English/EN)	2141	471 (22.00%)	679 (31.71%)	991 (46.29%)
TextBlob (English/EN)	2141	394 (18.40%)	945 (44.14%)	802 (37.46%)
TextBlob (German/DE)	4	0 (0.00%)	4 (100.00%)	0 (0.00%)

February 2024

Results

Based on the analysis of **1984** out of 2275 posts, the results are as follows:

	# of Posts	Negative Sentiment [-1..-0.05]	Neutral Sentiment (-0.05..0.05)	Positive Sentiment [0.05..1]
VADER (English/EN)	1982	419 (21.14%)	724 (36.53%)	839 (42.33%)
TextBlob (English/EN)	1982	357 (18.01%)	891 (44.95%)	734 (37.03%)
TextBlob (French/FR)	1	0 (0.00%)	1 (100.00%)	0 (0.00%)
TextBlob (German/DE)	1	0 (0.00%)	1 (100.00%)	0 (0.00%)

March 2024

Results

Based on the analysis of **2102** out of 2455 posts, the results are as follows:

	# of Posts	Negative Sentiment [-1..-0.05]	Neutral Sentiment (-0.05..0.05)	Positive Sentiment [0.05..1]
VADER (English/EN)	2102	331 (15.75%)	746 (35.49%)	1025 (48.76%)
TextBlob (English/EN)	2102	284 (13.51%)	1107 (52.66%)	711 (33.82%)

April 2024

Results

Based on the analysis of **2102** out of 2455 posts, the results are as follows:

	# of Posts	Negative Sentiment [-1..-0.05]	Neutral Sentiment (-0.05..0.05)	Positive Sentiment [0.05..1]
VADER (English/EN)	2102	331 (15.75%)	746 (35.49%)	1025 (48.76%)
TextBlob (English/EN)	2102	284 (13.51%)	1107 (52.66%)	711 (33.82%)

May 2024

Source: Communalytic

effect of service reliability on public support for transport services (Boontarig, 2018). In addition to validating this overall correlation, the results highlight a practical implication. During service disruptions, policymakers and operators should anticipate a surge in negative online sentiment and address complaints transparently to prevent further erosion of public trust.

A key aspect of this study involved applying both TextBlob and VADER to quantify public opinion towards TransJakarta. For example, in September 2023, VADER classified 42.14% of posts as positive, compared to 35.21% using TextBlob. This trend continued throughout the entire dataset, with VADER consistently generating higher positivity scores. This discrepancy is largely due to methodological design: VADER's lexicographic approach is engineered to recognise linguistic proxies indicating positivity, whereas TextBlob's polarity-subjectivity model tends to classify posts more frequently as neutral or mixed (Vasquez, 2021). These systematically varied results must be treated with caution by public sector practitioners. As these sentiment findings may be used to support policy narratives, there is an ethical responsibility to interpret them transparently and avoid selectively using one methodology over another to fit a predetermined conclusion (Engstrand, 2024; Yuan, 2023).

Extending this comparison, Cohen's Kappa coefficient showed only moderate agreement between VADER and TextBlob, reinforcing the observation that each tool interprets sentiment differently. This shows the risk of relying exclusively on any single method (Vasquez, 2021). For researchers, the implication is methodological: triangulation or ensemble approaches can enhance robustness (Bordoloi, 2023; Mao, 2024). For practitioners, it shows that sentiment analysis should be treated as an indicative lens rather than a definitive measure in ensuring that policy responses remain grounded in a balanced interpretation of public opinion (Engstrand, 2024; Yuan, 2023)

Building on this, the confusion matrices show that VADER and TextBlob generally agree on the classification of positive and neutral posts but diverge sharply in their treatment of negative sentiment. In September 2023, for example, VADER identified 544 posts as negative compared to TextBlob's 333. Similar discrepancies appeared in November 2023. This reflects a broader trend noted in prior studies: while TextBlob's thresholds for negativity tend to be more conservative, machine learning algorithms like VADER can overemphasise positive sentiment due to the high prevalence of polite or neutral language in online discourse (He et al., 2022). Such discrepancies underline that negative sentiment is particularly difficult to reliably capture, reinforcing the importance of cautious interpretation by researchers and practitioners.

Current sentiment analysis tools often struggle to accurately interpret the nuances of human communication due to wide variations in expression. VADER, which relies on lexical analysis, can produce exaggerated positive or negative outputs, while TextBlob's stricter thresholds often classify complex or ambiguous expressions as neutral. The analysis of public transport sentiment reveals notable challenges in this regard, as passengers frequently express frustration through sarcasm or subtle language (Jones, 2022; Pang, 2008). Therefore, public transport operators should investigate 'neutral' sentiment streams thoroughly, as these may contain subdued expressions of dissatisfaction, particularly in relation to service disruptions.

Sentiment analysis of public transport opinions in Jakarta faces complex challenges due to the city's linguistically diverse population. Tools like VADER and TextBlob struggle to recognise informal Indonesian language slang and colloquial expressions, as their lexicons lack these elements, leading to classification inaccuracies. These sentiment

Table 5.
Comparative Analysis Using VADER and TextBlob

Confusion Matrix (excluding duplicates)

The following table shows both agreement and disagreement counts across sentiment labels as determined by VADER and TextBlob.

	VADER - Negative [-1..-0.05]	VADER - Neutral (-0.05..0.05)	VADER - Positive [0.05..1]
TextBlob - Negative [-1..-0.05]	205	49	82
TextBlob - Neutral (-0.05..0.05)	184	326	326
TextBlob - Positive [0.05..1]	106	146	433

November 2023

Confusion Matrix (excluding duplicates)

The following table shows both agreement and disagreement counts across sentiment labels as determined by VADER and TextBlob.

	VADER - Negative [-1..-0.05]	VADER - Neutral (-0.05..0.05)	VADER - Positive [0.05..1]
TextBlob - Negative [-1..-0.05]	135	89	96
TextBlob - Neutral (-0.05..0.05)	144	403	393
TextBlob - Positive [0.05..1]	134	155	440

December 2023

Confusion Matrix (excluding duplicates)

The following table shows both agreement and disagreement counts across sentiment labels as determined by VADER and TextBlob.

	VADER - Negative [-1..-0.05]	VADER - Neutral (-0.05..0.05)	VADER - Positive [0.05..1]
TextBlob - Negative [-1..-0.05]	166	84	88
TextBlob - Neutral (-0.05..0.05)	137	437	391
TextBlob - Positive [0.05..1]	126	133	536

January 2024

Confusion Matrix (excluding duplicates)

The following table shows both agreement and disagreement counts across sentiment labels as determined by VADER and TextBlob.

	VADER - Negative [-1..-0.05]	VADER - Neutral (-0.05..0.05)	VADER - Positive [0.05..1]
TextBlob - Negative [-1..-0.05]	162	107	109
TextBlob - Neutral (-0.05..0.05)	173	382	390
TextBlob - Positive [0.05..1]	135	170	491

February 2024

Confusion Matrix (excluding duplicates)

The following table shows both agreement and disagreement counts across sentiment labels as determined by VADER and TextBlob.

	VADER - Negative [-1..-0.05]	VADER - Neutral (-0.05..0.05)	VADER - Positive [0.05..1]
TextBlob - Negative [-1..-0.05]	140	76	78
TextBlob - Neutral (-0.05..0.05)	164	404	309
TextBlob - Positive [0.05..1]	113	165	446

March 2024

Confusion Matrix (excluding duplicates)

The following table shows both agreement and disagreement counts across sentiment labels as determined by VADER and TextBlob.

	VADER - Negative [-1..-0.05]	VADER - Neutral (-0.05..0.05)	VADER - Positive [0.05..1]
TextBlob - Negative [-1..-0.05]	123	65	80
TextBlob - Neutral (-0.05..0.05)	115	515	476
TextBlob - Positive [0.05..1]	93	145	468

April 2024

Confusion Matrix (excluding duplicates)

The following table shows both agreement and disagreement counts across sentiment labels as determined by VADER and TextBlob.

	VADER - Negative [-1..-0.05]	VADER - Neutral (-0.05..0.05)	VADER - Positive [0.05..1]
TextBlob - Negative [-1..-0.05]	123	65	80
TextBlob - Neutral (-0.05..0.05)	115	515	476
TextBlob - Positive [0.05..1]	93	145	468

May 2024

Source: Communalytic

analysis platforms, designed primarily for English and international markets, often fail to capture specific cultural and contextual signals (Jurafsky, 2020). Future applications would benefit from building custom dictionaries that include regional vocabulary and adjusting classification thresholds specifically for Indonesian use to improve the accuracy of public discourse analysis.

While automated sentiment analysis offers valuable insights into public opinion, it is essential to acknowledge its limitations. Both VADER and TextBlob rely on pre-set lexical dictionaries, which are generally poor at identifying sarcasm or idiomatic expressions (Gardner, 2021). Another limitation of this study is the prominent presence of official TransJakarta X accounts, which, by their nature, rarely express negative sentiment. This introduces a structural bias that artificially inflates the proportion of positive sentiment in the dataset. To mitigate similar challenges, many scholars recommend supplementing automated analysis with manual verification, allowing for a more nuanced and contextually informed understanding of public opinion (Olsen, 2022)

The dominance of official TransJakarta accounts among the top contributors also highlights how institutional voices can shape online discourse. While these accounts play a valuable role in sharing service announcements and responding to user queries in an effort to enhance accountability and interaction, their high volume of posts can inadvertently marginalise organic user contributions, potentially suppressing critical voices. Feldman (2013) suggests that excluding institutional accounts from future sentiment analyses could yield a more accurate approximation of genuine public opinion.

Even further at the institutional control level, the evidence also reveals regular correlation between public opinion and large service events. Peaks in online discussion frequently coincided with major service changes, such as those implemented in October 2023, which attracted intense levels of both negative and positive commentary. These trends support previous findings that social media debate is largely event-driven, and that service disruptions or changes are key catalysts for increased public discourse (Hu, 2019; Broomfield & Reutter, 2021; Chen Q. M., 2020). For policymakers and operators, this opens up the potential of using sentiment analysis for real-time monitoring, enabling agencies to anticipate public response and react swiftly when implementing service changes.

Another key finding concerns the comparative predictive power of social media relative to traditional surveys. While surveys provide detailed, retrospective insights from defined sample groups, social media generates a contemporaneous stream of public opinion that captures real-time shifts in mood. This creates a feedback loop through which services can be calibrated and issues addressed proactively, before dissatisfaction becomes entrenched (Chen, 2014). For an operator like TransJakarta, whose brand is heavily influenced by public perception, this capacity for near-real-time responsiveness can enhance service legitimacy and user confidence.

This study also highlights a broader methodological shift in how public opinion can be examined. Through machine learning tools such as VADER and TextBlob, unstructured social media data can be processed at a scale unachievable through traditional methods, opening new possibilities for identifying large-scale sentiment patterns. However, the limitations of these tools remain evident; they often struggle to detect sarcasm, irony, and other nuanced expressions, making human oversight indispensable (Cambria, 2017). The implication is not to abandon automated analysis, but to integrate it within hybrid approaches that balance computational efficiency with interpretive depth.

Even with these advancements, challenges remain in identifying veiled negative opinions. In Indonesia, cultural norms often encourage the expression of grievances through 'polite' euphemisms or indirect language, which can be misinterpreted by tools like VADER and TextBlob as positive sentiment. This societal preference for indirect communication has concrete implications for automated analysis: satisfaction metrics may be systematically overstated, particularly in sensitive areas such as public transport (Jones, 2022). Policymakers must recognise this risk, as overlooking subtle dissatisfaction can create a misleadingly optimistic picture of public opinion and damage trust if underlying grievances are ignored.

To address these weaknesses, manual sentiment analysis has been employed to complement automated processing. Although more time- and labour-intensive, manual coding can capture sarcasm, irony, and culturally specific references that algorithms often miss (Gardner, 2021; Jim. J. R, 2024). This is especially important in social media analysis, where colloquial language, slang, and humour frequently lead to misclassification. As illustrated in Table 6, incorporating human verification not only corrected errors but also established a more credible baseline for interpreting public sentiment. This approach enhances validity by combining machine efficiency with human judgment (Olsen, 2022).

Manual inspection also revealed specific instances where automated tools failed to detect sarcasm. For example, posts such as "*Great job, TransJakarta! Another bus delay, just what I needed!*" were routinely misclassified as positive due to the presence of words like "great" and "job." Human coders, however, correctly identified these as expressions of frustration (Jones, 2022). By systematically correcting such errors, manual verification produced results that more accurately reflected public sentiment beyond the current capabilities of algorithmic interpretation.

Aside from sarcasm, manual coding also captured cultural and situational subtleties that automated tools consistently overlooked. Indonesian social media users frequently employ colloquialisms, local expressions, or culturally embedded phrases that are not adequately processed by the dictionaries of VADER and TextBlob. Human annotators who were familiar with these linguistic nuances were able to interpret the intended sentiment more accurately (Borate, 2023). Cultural sensitivity is essential in sentiment analysis, as universal lexicons risk oversimplifying context-specific meanings and misrepresenting public opinion.

Although time- and resource-intensive, combining automated sentiment analysis

Table 6.
Manual Analysis

Date	Total Data	Analysed Data	Negative Sentiment	Neutral Sentiment	Positive Sentiment
September 2023	2,278	2,278	378	943	957
October 2023	2,333	2,086	533	453	1,100
November 2023	2,250	1,864	437	749	687
December 2023	2,351	2,040	413	967	651
January 2024	2,463	2,147	423	686	1,038
February 2024	2,452	2,141	512	896	733
March 2024	2,275	1,982	434	687	861
April 2024	2,455	2,102	368	717	1,017
May 2024	2,455	2,102	323	769	1,010
Total	**21,312**	**18,742**	**3,821**	**6,867**	**8,054**

Source: Authors

with manual verification produces a more credible understanding of public opinion. While automated tools excel in speed and scalability, they struggle with linguistic subtlety; human coders are capable of correcting these deficiencies and capturing deeper layers of meaning. Manual review of a subsample of posts allowed previous researchers to identify and correct misclassifications due to sarcasm and ambiguous expressions (Gardner M. , 2021). Through this hybrid process, sentiment classification achieves greater accuracy by allowing human nuance to emerge (Olsen, 2022).

Having considered these methodological points, it is valuable to reflect on their practical applications. Sentiment analysis offers transportation agencies significant potential for service improvement and enhanced public engagement. Perhaps the most direct application is in service refinement: by continuously monitoring user messages, agencies can identify recurring issues, such as delays or disruptions on specific routes, and respond promptly. This not only addresses immediate grievances in the short term but also establishes a feedback system that fosters user satisfaction and confidence over the longer term (Muhammad, 2020). For policymakers, this approach provides not only a diagnostic tool but also a means of foresight, enabling proactive improvements in service delivery.

In addition to capturing the views of existing riders, sentiment analysis also accounts for the attitudes of non-riders, who have often been excluded from standard surveys. By analysing social media, it becomes possible to gather voluntary feedback from individuals who do not yet use public transport, revealing reasons such as concerns over reliability, safety, or comfort. Such insights are valuable not only for operators like TransJakarta but also for new agencies seeking to attract riders, expand service coverage, and improve overall inclusivity (Boontarig, 2018).

Although these findings are based on the case of TransJakarta, their applicability extends much further. Cities worldwide are grappling with the challenges of rapid urbanisation and the growing demand for user-friendly, responsive public transport. Web-based sentiment analysis of social media offers an efficient way to track public opinion in real time, enabling transport agencies to respond more effectively and rapidly (Liu M. , 2023; Pani & Mourya, 2023; Shahat Osman, 2021). Transportation agencies could enhance their level of user satisfaction and efficiency (Schintler, 2014; Rocca, 2020), and strengthen public trust through more evidence-based decision-making (Paskarina, 2023).

Looking ahead, there are numerous avenues for further research to build on these results. Methodologically, future work could integrate sentiment analysis with more advanced NLP models based on deep learning in order to better interpret tone, context, and subtle linguistic cues. In terms of scope, expanding data collection to include platforms such as Facebook or Instagram alongside X could yield a more representative picture of public opinion, accounting for variations in communication styles and demographics across different social media sites (Saraf, 2024). Such refinements would enhance the validity and utility of sentiment analysis, be it within transport policy or across broader public administration contexts.

Conclusion

This study analyses public sentiment towards TransJakarta services from September 2023 to May 2024 using data from X. Using Communalytic, VADER, and TextBlob, supported by word frequency analysis, word clouds, and manual verification, we demonstrate how social media can serve as a rapid and effective tool for monitoring public service delivery. Our findings indicate that sentiment fluctuates in response to operational disruptions and policy changes, with consistent discrepancies between VADER and TextBlob classifications. These differences show the strengths and limitations of automated sentiment analysis: while machine learning tools allowed for efficient large-scale data processing, they struggled with linguistic subtleties such as sarcasm or indirect expression, which only manual checks were able to capture. Thus, the hybrid approach adopted in this study offers a more reliable method for interpreting public opinion.

Beyond methodological contributions, the study shows the practical value of sentiment analysis for policymakers. By capturing real-time public reactions, transport agencies can identify emerging issues more quickly and respond to concerns proactively, to strengthen service delivery and public trust. The study also emphasises the necessity of balancing automated tools with human oversight to ensure nuanced and contextually sensitive interpretations. In doing so, our findings advance the literature on big data in public administration and present a simplified yet robust framework for more accessible sentiment analysis, which can be applied beyond the Indonesian context in ongoing policy evaluation and public service improvement.

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