

Sentiment Polarity and Network Structure in The '*Karo Bukan Batak*' Twitter Discourse: A NodeXL and Python-Based Text Mining Study of Local-Language Expressions

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Abstract

This study examines digital identity contestation within the “Karo Bukan Batak” discourse on Twitter/X, with particular attention to how local-language expressions drive affective polarization in the Global South. Employing an integrated computational social science design, the research combines macro-level Social Network Analysis (SNA) using NodeXL with a micro-level Support Vector Machine (SVM) sentiment classification model calibrated through a data-driven, local-language lexicon. The SVM model effectively addresses code-mixing and regional slang, achieving an overall accuracy of 80.00% and an F1-score of 0.90 in detecting negative sentiments associated with algorithmic “othering.” Structurally, the network of 14,688 users exhibits a weak-tie architecture, characterized by a low graph density and high modularity, which fragments the discourse into thousands of isolated echo chambers with limited cross-group interaction. Betweenness centrality analysis identifies a range of gatekeepers, including political figures, generative Artificial Intelligence, and anonymous counterpublic arenas, who employ ethnic hashtags to reinforce in-group boundaries. The findings suggest that engagement-driven platform architectures do not merely disseminate information but also intensify societal segregation by incentivizing digital political labor. The study highlights the need for ethnolinguistically adaptive content moderation frameworks and stronger algorithmic accountability to preserve social cohesion in multicultural societies.

1. Introduction

The evolution of social media has fundamentally altered the landscape of political and ethnic communication, positioning these platforms as central arenas for the articulation, negotiation, and contestation of collective identities. In many countries within the Global South, including Indonesia, platforms such as Twitter/X function as spaces where primordial identities, particularly ethnic and religious, are reactivated through highly emotional and easily politicised user-generated content (Katsarou et al. 2021; Kydros et al. 2021). Within this context, sentiment analysis and social media network analysis have emerged as essential tools for examining how identity conflicts are mobilised and sustained in digital environments (Poleksic and Martincic-Ipsic 2023; Yuda Kusuma et al. 2023).

A well-known example of digital identity contestation in Indonesia is the “Karo Bukan Batak” movement. This issue began with the Dutch colonial government’s classification of ethnic groups in North Sumatra. The Karo community resisted being grouped under the broad label of “Batak” and worked to assert their own ethnic identity, setting themselves apart from the dominant Batak group. They used different forms of communication, including online campaigns, to make their case. On Twitter/X, slogans and hashtags about “Karo Bukan Batak” have become a key way for people to debate who belongs to which group. These online discussions also show how local identity politics can be shaped and spread by social media algorithms (Katsarou et al. 2021; Ahmed et al. 2024).

The architectural design of Twitter/X accelerates information circulation through real-time feeds, character limits, and features such as retweets, mentions, and hashtags, which facilitate the formation

of weak ties among users. This weak-tie network structure enables the emergence of relatively loose discursive clusters that remain highly susceptible to affective polarization, particularly when sensitive identity issues arise (Charlton et al. 2016; Ahmed et al. 2024). Several studies demonstrate that algorithms prioritising engagement amplify highly emotional content, including anger, hatred, and antagonistic sentiments. This amplification reinforces echo chambers and intensifies the affective divide between groups (Katsarou et al. 2021; Kydros et al. 2021; H. Zhou et al. 2024).

Social Network Analysis (SNA) provides a robust framework for mapping the structure and dynamics of conflict networks. For example, NodeXL analysis of the “Karo Bukan Batak” discourse from 2013 to 2025 demonstrates a highly segmented network characterized by low graph density, high modularity, and thousands of interconnected components that function as echo chambers. These results are consistent with previous research that associates network fragmentation, community formation, and discourse polarization with modularity metrics and the presence of large communities in social networks (Blondel et al. 2008; Poleksic and Martincic-Ipsic 2023). Although SNA effectively reveals structural patterns and identifies the positions of key actors within networks, such as users with high betweenness centrality, it remains limited in its capacity to capture the affective qualities of conversations, especially when messages are expressed in local languages and slang.

The literature on sentiment analysis of Twitter data has expanded rapidly, employing approaches that range from lexicon-based methods to deep learning models. Foundational studies, including those by Pang et al. (2002;2008) and Hu and Liu (2004), illustrate the classification of opinion polarity using textual features and sentiment dictionaries. Lexical resources such as SentiWordNet (Baccianella et al. 2010) and its subsequent extensions (Mehta and Chandra 2019) have further advanced dictionary-based polarity measurement. In social media contexts, sentiment analysis has been applied to domains such as health, politics, public policy, and crisis communication, notably during the Covid-19 pandemic and vaccination campaigns (Gupta et al. 2021; Kydros et al. 2021; Mohamed Ridhwan and Hargreaves 2021; Roe et al. 2021; Turner et al. 2021). More recently, advanced natural language processing models based on BERT and related architectures have been utilized to classify sentiment and stance in complex discourses, including climate change, virus variants, and contentious policy issues (Marrapu et al. 2025; Zhang 2025).

However, most existing studies concentrate on global languages, particularly English, and Global North contexts, while providing limited analysis of sentiment expression in local languages, dialects, or code-mixing prevalent in Indonesia. Research on political sentiment in developing countries and multilingual environments demonstrates that generic lexicons and models frequently fail to capture emotional nuances, irony, sarcasm, or identity-based hate speech embedded in local contexts (Obagbuwa and Chibaya 2024; Balcarová et al. 2025; M. Dixit et al. 2025). This limitation is especially evident when examining issues related to ethnic contestation, as the relevant categories, labels, and terms are often highly contextual and absent from standard sentiment dictionaries (Fornacciari et al. 2015; Basili et al. 2017).

Two primary gaps exist in the discourse analysis of “Karo Bukan Batak.” First, few studies simultaneously integrate network structure analysis, such as those using NodeXL or other social network analysis (SNA) tools, with text-mining-based sentiment analysis to investigate the distribution of affective polarization within networks. Second, sentiment analysis methods that are sensitive to local languages—including Karo, Batak, and Indonesian slang—remain underdeveloped in the context of ethnic identity conflicts. Integrating these two dimensions is essential for elucidating how the configuration of weak-tie networks on Twitter interacts with sentiment intensity and the production of “digital political labour” in either intensifying or mitigating identity conflicts.

Addressing the identified context and research gaps, the present study, titled “Sentiment Polarity and Network Structure in the ‘Karo Bukan Batak’ Twitter Discourse: A NodeXL and Python-Based Text Mining Study of Local-Language Expressions,” integrates NodeXL-based social network analysis with Python-based sentiment analysis on a corpus of tweets featuring local language expressions. The research objectives are as follows: (1) to map the network structure of the “Karo Bukan Batak” discourse on Twitter/X, including the identification of communities, key actors, and connectivity patterns; (2) to classify the sentiment polarity of tweets containing Karo, Batak, and Indonesian slang expressions; and (3) to analyse the relationship between network structure patterns and sentiment distribution in order to assess whether this discourse contributes to the escalation of identity conflicts or facilitates depolarization. By focusing on the Global South context, this study aims to advance the literature on algorithmic political communication, affective polarization, and sentiment analysis of local languages on social media.

2. Literature Review

Recent developments in social media studies demonstrate that Twitter/X serves as a critical platform for examining the formation of public opinion, public sentiment, and identity contestation within digital communication environments. Numerous studies employ Twitter data to map the dynamics of public discourse on political issues, health, crises, and policy, as the platform facilitates real-time observation of interactions, affect, and large-scale narrative dissemination. Within this context, the present literature review positions research on the “Karo Bukan Batak” discourse across three primary strands: sentiment analysis on social media, the integration of sentiment analysis with social network analysis, and the challenges associated with analysing local languages in digital identity conflicts.

2.1 Sentiment analysis on social media

Pang et al. (2002) established foundational work in this field by demonstrating that machine learning techniques can systematically classify opinion polarity. Pang and Lee (2008) subsequently affirmed opinion mining as a key branch of information retrieval and natural language processing. In the following phase, Hu and Liu (2004) showed that opinion extraction from textual data enables the summarisation of user evaluations. Additionally, Baccianella et al. (2010) introduced SentiWordNet 3.0, a highly influential lexical resource for dictionary-based sentiment analysis.

Sentiment analysis in the Twitter/X environment presents greater challenges due to the brevity, unstructured nature, frequent abbreviations, and the presence of irony, emojis, or multilingual content. Fernández-Gavilanes et al. (2015), Vilares et al. (2015), and Htait et al. (2017) demonstrate that sentiment classification performance on Twitter is significantly affected by preprocessing, linguistic feature selection, and model adaptation to tweet-specific characteristics. As the field has progressed, methodologies have shifted from exclusive reliance on lexicons to the integration of machine learning and deep learning, thereby improving models' contextual sensitivity. Ahmed et al. (2024) highlight that combining natural language processing (NLP) and deep learning enhances real-time sentiment analysis, while Zhang (2025) shows that fine-tuned BERT models are effective for sentiment and stance classification on complex topics such as climate change.

The scope of sentiment analysis applications on social media continues to expand. Research by Gupta et al. (2021), Mohamed Ridhwan and Hargreaves (2021), Roe et al. (2021), and Marrapu et al. (2025) demonstrates that Twitter sentiment can effectively gauge public responses to the pandemic, vaccination, and health crises. Additionally, Hu and Liu (2004) show that consumer opinions can be systematically extracted and summarized from online reviews using a feature-based approach and lexical polarity. In the context of political issues and public opinion, Ayma Quirita et al. (2024), Pugsee et al. (2025), and Bernábe-Loranca et al. (2022) demonstrate that sentiment analysis can reveal voters' affective tendencies, the intensity of support, and patterns of contention within digital political discourse. Collectively, these findings indicate that sentiment analysis is valuable not only for classifying emotions but also for elucidating the broader social dynamics underlying the production and circulation of online messages.

2.2 Integration of sentiment and network analysis

Sentiment analysis helps us understand the emotional content of conversations, but it does not show how messages travel through social networks. Because of this, researchers have started to combine sentiment analysis with social network analysis to better explain how message polarity, community structure, and the roles of different people in the network are connected. Fornacciari et al. (2015) were among the first to highlight the value of using both methods together on Twitter, since the relationships between users can reveal how opinions and emotions spread in the network. This integrated approach has since developed across various empirical contexts.

Nozza et al. (2015) demonstrated that latent representation models in heterogeneous social networks capture sentiment more effectively when user relationship structures are considered. Katsarou et al. (2021) established a close association between sentiment polarization in online social networks and the flow of hate speech as well as group segregation. Additionally, Poleksic and Martincic-Ipsic (2023) showed that integrating sentiment analysis with social network analysis enhances the understanding of narrative dynamics during the Russia-Ukraine conflict.

Yuda Kusuma et al. (2023) used social network analysis to map Twitter discussions about the XBB.1.5 variant, showing that network structure helps explain how conversations happen. These patterns can

then be studied further with content and sentiment analysis. This is relevant to the current research, since the “Karo Bukan Batak” discussion involves not just the text but also how relationships, groups, and influence are organized online.

Early NodeXL data in the research draft show very low graph density, high modularity, and thousands of connected parts, which suggests the network is fragmented and echo chambers may form. This matches Blondel et al. (2008), who highlight the value of community detection for understanding large networks. It also supports the idea that polarised conversations should be studied not just by looking at messages, but also by examining how people are connected. Using NodeXL for network analysis together with Python for sentiment analysis is therefore a good way to study the link between network structure and emotional tone in ethnic identity discussions.

2.3 Local Languages and The Context of Digital Identity

A significant limitation of mainstream sentiment analysis literature is its predominant reliance on English-language data and contexts from the Global North. However, a substantial portion of social media discourse occurs in local languages, regional dialects, slang, or mixed codes, which are often inadequately captured by generic lexicons. Basili et al. (2017) highlight the necessity of developing a dynamic polarity lexicon for advanced social media analytics, while Mehta and Chandra (2019) show that incorporating contextual valence shifters into SentiWordNet improves the analysis's sensitivity to contextual shifts in meaning.

Khairani and Wiradnyana (2023) demonstrate that the genealogical folklore of the Batak Toba, Nias, and Gayo peoples serves as a mechanism for legitimising power, asserting territorial claims, and affirming ethnic identity. These orally transmitted origin narratives delineate the boundaries between ‘us’ and ‘them’ and influence the formation of traditional authority structures. Kristiyanti et al. (2024) demonstrate that even within the Indonesian context, issues of data imbalance and linguistic variation pose serious challenges for sentiment analysis. Obagbuwa and Chibaya (2024), Balcarová et al. (2025) and Dixit (2024) also demonstrate that model accuracy is heavily determined by the system’s ability to interpret context, domain, and forms of expression that are not always literal. In the case of the “Karo Bukan Batak” discourse, this issue is further complicated by the fact that terms, sarcasm, and emotional expressions may appear in Karo, Batak, informal Indonesian, and combinations thereof.

A Python-based text mining approach is required for this research to facilitate data cleaning, normalisation, preservation of local terms, and adaptation of dictionaries or classification models to specific ethnolinguistic contexts. This methodology is consistent with recent studies that position sentiment analysis within computational social science, emphasizing sensitivity to domain-specific contexts such as health, politics, and public identity on social media. Incorporating local languages into the analysis seeks to address a gap in the literature regarding the relationship between local ethnic expressions, sentiment polarity, and digital network structures in Indonesia.

3. Methodology

3.1 Research Design

This research adopts a computational social science methodology with a quantitative framework, integrating social network analysis (SNA) and sentiment analysis based on text mining. SNA facilitates the mapping of network structures and communities within the “Karo Bukan Batak” discourse, while sentiment analysis classifies the affective polarity of tweets containing local language expressions and code-mixing. This integrative approach is consistent with contemporary research trends that combine network representations and sentiment models to examine the dynamics of conflict and polarization on social media (Fornacciari et al. 2015; Nozza et al. 2015; Poleksic and Martincic-Ipsic 2023).

3.2 Data Sources and Collection Procedures

The research data comprises public tweets from the Twitter/X platform that include keywords and hashtags associated with the discourse “Karo Bukan Batak.” These keywords encompass combinations of the terms Karo, Batak, and commonly used Indonesian language variations. Data collection was performed using NodeXL, which extracted conversation networks based on specified keywords during the period from 21 June 2013 to 22 August 2025. This process produced a dataset of vertices (users), edges (interactions), and tweet texts. The use of Twitter data to gauge public opinion and attitudes has been well established in research on elections, health, and policy, underscoring Twitter’s utility as a real-time public discourse laboratory (Mahajan and Gupta 2021; Mohamed Ridhwan and Hargreaves 2021; Ayma Quirita et al. 2024)).

To ensure data quality and relevance, several inclusion and exclusion criteria were applied. Tweets lacking the main keywords, identical duplicates, and retweets without comments were excluded from the sentiment analysis corpus. Tweets originating from accounts reported as blocked or deleted by the platform after the data collection period were retained if the text remained available in the NodeXL extraction results, consistent with established practices in historical Twitter stream research.

3.2.1 Ethical Considerations and Data Protection

All data for this study were obtained exclusively from publicly accessible Twitter/X posts, in accordance with the platform’s Terms of Service and relevant data protection regulations. Usernames, profile information, and direct identifiers were excluded from the analytical dataset. Only aggregated network metrics and anonymised examples are presented. No effort was made to deanonymise users, contact account holders, or access private messages. Because the study examines public discourse without intervention or interaction with human subjects, it qualifies as minimal-risk observational research. Nevertheless, the study was designed to prevent harm, stigmatisation, or undue targeting of individuals or communities, particularly with respect to sensitive ethnic and identity markers.

3.3 Social Network Analysis (NodeXL)

The social network analysis examines the structure of relationships among Twitter/X accounts participating in the “Karo Bukan Batak” discourse. NodeXL is used to construct a directed graph,

modelling interactions such as replies, mentions, and retweets as edges between user accounts represented as vertices. Key metrics calculated include graph density, the number of connected components, modularity, and centrality, with particular emphasis on betweenness centrality, to identify communities and bridge actors within the network. This methodology is consistent with established social network analysis practices on Twitter, which employ community metrics and centrality to reveal patterns of fragmentation and polarization (Blondel et al. 2008; Poleksic and Martincic-Ipsic 2023; Yuda Kusuma et al. 2023).

Community detection is conducted using an algorithm based on modularity optimisation, resulting in the division of the graph into groups of users that are more densely connected internally than externally. A high modularity value is interpreted as strong evidence of network segregation into echo chambers, as described in the literature on affective polarization in social networks (Katsarou et al. 2021; Kydros et al. 2021). Additionally, the results of community detection are linked to sentiment distributions to assess whether specific groups are characterised by particular affective polarities.

The diagram above illustrates an integrated computational workflow. The process begins with the extraction of macro-level structural data using NodeXL, followed by micro-level textual analysis (text cleaning, local lexicon, and SVM) using Python, culminating in the final stage where message polarity is combined with network proximity metrics to comprehensively identify patterns of affective polarization.

3.4 Text Pre-processing and Sentiment Analysis

The text pre-processing stage was implemented in a Python environment using tweet text columns extracted from NodeXL. The procedure included character normalisation by converting all text to lowercase, removal of URLs, usernames (@user), hashtags (#), irrelevant numbers, and special characters, as well as the consolidation of double spaces. Tokenisation and the removal of common stopwords were also performed, with specific adjustments to retain important terms in the Karo and Batak languages and Indonesian slang as units of analysis. These pre-processing steps are consistent with established practices in Twitter sentiment analysis, which highlight the importance of text cleaning for enhancing classification model performance (Fernández-Gavilanes et al. 2015; Vilares et al. 2015; Htait et al. 2017).

After pre-processing, sentiment analysis was performed using a supervised learning approach based on a subset of labelled data. The sentiment classification model incorporated two primary polarity categories, positive and negative, as well as a neutral class, depending on data distribution and analytical requirements. Previous research in Twitter sentiment analysis demonstrates that feature selection methods, such as n-grams, distributional representations, or embeddings, and classification algorithms, including support vector machines, logistic regression, or neural networks, significantly influence result accuracy (Pang et al. 2002; Ahmed et al. 2024; Zhang 2025). The present study adapts these methodologies by emphasizing the representation of identity-sensitive local terms.

In the context of local and mixed languages, this study employs a combination of lexical resources and machine learning techniques. SentiWordNet 3.0, developed by Baccianella et al. (2010), and its extension with contextual valence shifters (Mehta and Chandra 2019), serve as initial references. However, these resources require adaptation due to the presence of non-English languages in the research corpus. Therefore, portions of the labelling process and model training were conducted in a data-driven manner using a corpus containing Karo and Batak language expressions. This approach aligns with domain adaptation practices used in sentiment studies within specialised contexts such as healthcare and public policy (Walsh et al. 2024; H. Zhou et al. 2024). Before sentiment classification using machine learning algorithms, the Twitter/X text data corpus underwent preprocessing in a Python environment.

The cleaning process includes normalising text to lowercase, removing links (URLs), usernames (@), hashtags (#), numbers, special characters, and consolidating double spaces. During stopword removal, specific adjustments ensured that cultural terms in the Karo and Batak languages, as well as Indonesian slang, were retained as units of analysis. This approach preserves the contextual meaning of the tweets.

After data cleaning, a data-driven local-language lexicon is developed by extracting n-gram features, such as bigrams and trigrams, directly from users' tweets. Compiling this domain-specific lexicon is essential for capturing emotional nuances and local sentiments of othering that standard dictionaries do not detect, including identity-affirming phrases like "kalak karo" or statements that disparage certain groups. This local-language lexicon serves as the primary foundation for annotating training data, which is then used to train classification algorithms to predict message polarity at scale and with accuracy.

Table 1
Local-Language Lexicon Snippet

No	Language	Term / Phrase	Translation (Literal Meaning)	Context of Use on Twitter/X	Sentiment Label (Weight)
1	Indonesia	Karo bukan Batak	Karo is not part of Batak	Main slogan to assert the autonomous identity of the Karo and reject assimilation.	Negative towards Batak (-1) / Positive for Karo (+ 1)
2	Karo	Orang Karo	Karo people	Affirming <i>in-group</i> membership to mobilise identity solidarity.	Positive (+ 1)
3	Indonesia	Batak Tulen	Pure/native Batak	Used to reinforce a dominant Batak identity, sometimes to mock.	Negative (-1)
4	Mixed	Orang Karo hanya numpang	The Karo people are merely tagging along	Discriminatory language (<i>othering</i>) that demeans the Karo people.	Negative (-1)
5	Mixed	Pembatakan suku karo	Batakisation of the Karo	A term of resistance/criticism against the forced classification of the Karo people as Batak.	Negative (-1)
6	Karo	mejuah-juah	Greetings / Best wishes	A traditional greeting of the Karo people, expressing pride in and commitment to preserving their culture.	Positive (+ 1)
7	Karo	biang	Dog	A crude insult frequently used in the escalation of identity-based debates.	Negative (-1)

3.5 Addressing Data Imbalance and Evaluating Model Performance

Sentiment class distributions in social media data are frequently imbalanced, with neutral or negative classes typically dominating. To mitigate this issue, the present study implements class weighting and, when appropriate, moderate resampling techniques during model training. This methodology is informed by Kristiyanti et al. (2024), who highlight that unaddressed class imbalance can diminish a model's sensitivity to minority classes.

Model performance is assessed using accuracy, precision, recall, and F1 score metrics on a test set distinct from the training data. Employing multiple evaluation metrics provides a more comprehensive assessment of model performance, as recommended by comparative studies of models and embedding techniques in Twitter sentiment analysis (Muslim et al., 2020; Kancharapu and Ayyagari, 2023). Beyond

quantitative evaluation, manual inspection of labelled tweet examples was performed to verify that the model captured emotional nuances in both local and mixed languages, rather than memorising superficial patterns.

3.6. Integration of Network and Sentiment

The final stage of the methodology integrates findings from social network analysis and sentiment analysis. Sentiment polarity labels assigned to individual tweets are aggregated at both user and community levels, and subsequently linked to network metrics such as community modularity and actor centrality. This process facilitates the identification of relationships between structural positions and the dissemination of various sentiments. This integrated approach aligns with prior research employing both social network analysis and sentiment analysis to examine polarization and the propagation of hate speech within social networks (Nozza et al., 2015; Fornacciari et al., 2015; Katsarou et al., 2021). Through this method, the study elucidates not only the discourse surrounding Karo and Batak identities but also identifies the most influential actors in disseminating specific sentiments and reveals how these sentiments are clustered within the network.

4. Research Findings and Discussion

4.1: Sentiment Classification Results

Table 2
SVM Sentiment Classification Model Accuracy Report
(Classification Report)

Sentiment Class	Precision	Recall	F1-Score	Support
Negative	0.86	0.95	0.90	44
Neutral	1.00	0.47	0.64	17
Positive	0.61	0.74	0.67	19
Overall Accuracy			0.80	80
Macro Average	0.82	0.72	0.74	80
Weighted Average	0.83	0.80	0.79	80

To check how reliable the Machine Learning model is at classifying message polarity, we tested it with the Support Vector Machine (SVM) algorithm on 20% of the test data, which was 80 samples out of 400 manually annotated points. Table 2 shows that the model reached an overall accuracy of 80.00%. The algorithm was especially strong at identifying Negative sentiment, with a precision of 0.86 and a recall of 0.95. This led to a high F1-score of 0.90 for the Negative class.

These results are important because they show the system can accurately detect speech with signs of conflict, identity segregation (othering), and affective polarization, even when local dialects or slang are

used on Twitter/X. This robust performance in the majority negative class demonstrates that the model successfully navigated the common challenge of data imbalance without losing sensitivity to conflict-laden texts (Kristiyanti et al. 2024). Furthermore, by relying on multiple evaluation metrics (precision, recall, and F1-score), this approach provides a significantly more rigorous and comprehensive assessment of text classification quality than simple accuracy reports alone (Muslim et al. 2020; Kancharapu and A Ayyagari 2023). The model also performed reasonably well for the Neutral and Positive classes, with F1-scores of 0.64 and 0.67. After this evaluation, the model was used to predict sentiment in 12,853 interactions within the discourse network.

Figure 2 presents the sentiment landscape of the conversations following comprehensive text preprocessing and analysis using a Support Vector Machine (SVM) algorithm calibrated with a local language lexicon. This visualization displays the final sentiment distribution across 12,853 interactions within the “Karo Bukan Batak” discourse ecosystem. In contrast to standard built-in lexicon extraction methods in network analysis software, which are inherently susceptible to domain bias and frequently fail to detect regional dialects, this Python-based computational model accurately identifies local emotional nuances. Such performance underscores that sentiment classification on social media heavily relies on customized preprocessing, nuanced feature selection, and model adaptation to platform-specific and ethnolinguistic characteristics (Fernández-Gavilanes et al. 2015; Vilares et al. 2015; Htait et al. 2017).

The figure empirically demonstrates the proportions of utterances related to segregation, identity boundary assertion, and narratives of othering classified as Negative, as well as expressions of cultural pride in the Positive class and objective conversations in the Neutral class. This mapping is consistent with recent computational social science literature showing that extracting user-generated sentiments from localized, unstructured digital spaces is vital for revealing voters' affective tendencies and the true intensity of societal polarization (Bernábe-Loranca et al. 2022; Ayma Quirita et al. 2024; Pugsee et al. 2025). Ultimately, the effectiveness of this machine learning-based sentiment mapping underscores the necessity of integrating advanced text mining techniques to accurately measure the scale and depth of affective polarization in digital identity contests characterized by extensive use of local language and slang.

4.2. Network Structure and Centrality

Table 3
Overall Network Metrics

Network Metrics (<i>Graph Metrics</i>)	Value
<i>Vertices</i> (Number of Users)	14,688
<i>Total Edges</i> (Total Interactions)	23,778
<i>Connected Components</i> (Groups/Clusters)	6,691
<i>Graph Density</i>	0.000047
<i>Modularity</i>	0.500979

Network data extracted using NodeXL software facilitates visualization of the discourse landscape through comprehensive graph metrics, as shown in Table 3. The network ecosystem consists of 14,688 users (vertices) connected by 23,778 interactions (edges). This structural analysis confirms the defining characteristics of Weak-Tie communication on the Twitter/X platform, as evidenced by a very low Graph Density value of 0.000047. Such a structural pattern enables rapid information dissemination across loosely connected discursive clusters, yet it remains highly susceptible to fragmented narratives (Charlton et al. 2016; Ahmed et al. 2024).

The most notable finding is the network's Modularity, which is exceptionally high at 0.500979. A Modularity value near 0.5 empirically indicates pronounced partisan segregation, with users divided into 6,691 groups (connected components). In network science, such elevated modularity metrics and dense community formations are strongly associated with structural fragmentation and discourse polarization (Blondel et al. 2008; Poleksic and Martincic-Ipsic 2023). The substantial number of clusters identified in this graph suggests that the identity discourse is dominated by echo chambers. In these environments, users voluntarily confine themselves within algorithmic filter bubbles to reinforce in-group sentiments, resulting in minimal cross-group interaction and discourse that primarily circulates within individual communities (Katsarou et al. 2021; Kydros et al. 2021).

Table 4
List of Key Network Actors Based on Betweenness Centrality

No	User Account (Vertices)	Betweenness Centrality Score	Role / Context of Conversation in the Network	Majority Sentiment
1	@jokowi	7,604,994	Various factions frequently reference these symbols to seek political legitimacy, demand recognition of identity, such as traditional Karo or Batak attire, and as targets of criticism.	Mixed (Positive from supporters, Negative when polarization intensifies)
2	@grok	6,047,243	An Artificial Intelligence (AI) account is extensively tagged by users to test, validate, or translate the history and lexicon of the Toba Batak and Karo languages for the purpose of supporting debate outcomes.	Mixed (Often triggers negative sentiment when AI results spark conflict)
3	@alexanderdrspan	3,097,931	An individual who demonstrates strong partisan activity by engaging in debates and generating tension concerning demographic issues, historical conflicts, and religious sentiments (Christian/Muslim) between the Batak Toba and other ethnic groups.	Negative (High polarization / <i>Othering</i>)
4	@youtube	2,990,048	A platform entity that functions as an information bridge by sharing references to cultural videos, music, and traditional dance.	Positive / Neutral
5	@tanyakanrl	2,903,558	An anonymous confession account frequently initiates discussions that provoke intense debates about stereotypes associated with the Batak and Karo ethnic groups among Generation Z.	Negative
6	@tanyarlfe	2,745,809	Similar to @tanyakanrl, this platform functions as a counterpublic arena where an anonymous audience engages in discussions of ethnic sentiments.	Negative
7	@detikcom	2,484,894	A mainstream media portal is characterized by the frequent citation or sharing of its news stories to support partisan arguments.	Neutral
8	@nandebapakukaro	2,135,077	A prominent local community leader actively promotes the	Positive (<i>In-Group</i>)

No	User Account (Vertices)	Betweenness Centrality Score	Role / Context of Conversation in the Network	Majority Sentiment
			"Kalak Karo" identity and regularly collaborates with other local cultural organizations.	Affirmation)

To identify individuals who control and facilitate information flow within the discourse ecosystem, this study measured the Betweenness Centrality score for each user (vertex). Rather than simply quantifying tweet frequency, this metric identifies strategic gatekeeper actors located at critical intersections of information flows between segregated clusters. These actors serve as structural bridges that can either accelerate or suppress the spread of narratives across communities. Employing betweenness centrality to map network roles is a well-established approach in social network analysis on Twitter/X, as it reveals underlying patterns of systemic fragmentation and polarization. As indicated in Table 4, central actors in this network demonstrate highly diverse interaction patterns, confirming the extensive use of identity symbols in digital environments. This finding is consistent with previous empirical research, which shows that integrating actor centrality with contextual message polarity is essential for understanding how opinion leaders systematically drive the propagation of hate speech and group segregation within conflict-prone social networks (Fornacciari et al. 2015; Katsarou et al. 2021).

The @jokowi account (score 7,604,994) holds the most central position as the primary bridge within the network. This high degree of centrality is attributable to the account's association with a prominent political figure, who is often referenced as a source of legitimacy. Multiple groups, including both pro-Karo and pro-Batak factions, tag this account to demand cultural recognition, such as advocating for the wearing of traditional attire, which elicits both positive and negative responses. This phenomenon demonstrates that mainstream political figures are frequently utilized by digital factions to secure systemic validation and mobilize support within highly contested public spheres (Bernábe-Loranca et al. 2022; Ayma Quirita et al. 2024).

The Artificial Intelligence account @grok (score 6,047,243) occupies the second most central position and plays a significant role in the conflict arena. Partisan actors strategically use this AI to validate translations of local lexicons, such as the Toba Batak language, or to assess historical claims, actions that frequently intensify debates and increase negative sentiment. The prominent structural role of this large language model (LLM) entity highlights a paradigm shift in computational social science, as generative AI tools now function as active, non-human participants whose automated outputs can inadvertently exacerbate polarization in highly sensitive ethnolinguistic disputes (Ahmed et al. 2024).

The structural mapping of the "Karo Bukan Batak" discourse is visualized through a network sociogram (Fig. 3) extracted using NodeXL. Each point (node/vertex) on this graph represents a single user account, while the connecting lines (edges) represent directed communication interactions, such as retweets, replies, and mentions. Figure 3 visually confirms the high level of discourse fragmentation within the network. This ecosystem, involving 14,688 users, does not form a single unified discussion

space but is fragmented into dense, isolated clusters. This segmentation correlates with the network modularity metric of 0.500979, indicating that user groups have split into 6,691 sub-networks (connected components). The densely clustered nodes in some parts of the graph indicate high levels of in-group interaction among users sharing the same ideological or ethnic affiliations, while the scarcity of edges crossing between clusters shows a lack of cross-boundary dialogue. Such topological fragmentation aligns with foundational network dynamics where high modularity serves as a clear indicator of structural division and community segregation (Blondel et al. 2008; Poleksic and Martincic-Ipsic 2023).

This visualization empirically demonstrates the occurrence of the ‘echo chamber’ phenomenon, facilitated by the Weak-Tie architecture of the Twitter/X platform. Within the context of sentiment analysis and Social Identity Theory (SIT), this graph maps the anatomy of Affective Polarization. This localized isolation mirrors established theories of group behavior where digital platforms accelerate partisan divides by shielding users from out-group perspectives (Tajfel et al. 2001; Katsarou et al. 2021). Users voluntarily confine themselves within algorithmic bubbles (filter bubbles), where they constantly produce “digital political labor” to validate their own group’s sentiments whilst delegitimizing the identity of opposing groups. Thus, this sociogram confirms that digital platforms are not merely passive channels for the distribution of discourse, but structurally mediate the escalation of identity conflicts by isolating users and exacerbating segregation between them (Katsarou et al. 2021; Kydros et al. 2021; Q. Zhou et al. 2025)

4.3. The Network Structure of Discursive Contestation (NodeXL Analysis).

Social Network Analysis (SNA) provides a comprehensive overview of the discursive environment. Aggregate graph metrics indicate that the network ecosystem consists of 14,688 users (vertices) and 23,778 interactions (edges). This network structure exhibits the defining characteristics of Weak-Tie communication, as evidenced by a very low Graph Density of 0.000047 (4.76862×10^{-5}). Such a structural configuration is highly susceptible to affective polarization in the presence of sensitive identity friction (Charlton et al. 2016; Ahmed et al. 2024).

Conversely, the Modularity value is notably high at 0.500979. This elevated modularity empirically supports the presence of partisan segregation, resulting in 6,691 groups (connected components) that function as echo chambers. This finding aligns with previous research that associates high community modularity with fragmented social network polarization (Blondel et al. 2008; Poleksic and Martincic-Ipsic 2023).

Users with the highest Betweenness Centrality scores, serving as primary information bridges or gatekeepers within this fragmented landscape, include the accounts @jokowi (score 7,604,994), @grok (6,047,243), @alexanderdrspan (3,097,931), and @youtube (2,990,048). Central hashtags dominated the discourse, with #kalak_karo leading at 263 posts, followed by #batak (255 posts) and #toba (219 posts). These patterns demonstrate how partisan actors systematically deploy targeted metadata to reinforce sub-ethnic identity boundaries and intensify group polarization (Katsarou et al. 2021; Kydros et al. 2021).

While the built-in network analysis tool NodeXL exhibits limitations in automatically classifying sentiment polarity for local languages, its raw data extraction capability remains empirically robust for recording discourse volume and trends at a macro level. Figure 4 demonstrates that the Word Cloud and Word Time Grid visualizations indicate a high prevalence of ethnicity-specific lexicon within the conversational network. Frequency calculations show that the term "Batak" dominates the discourse with 12,146 occurrences, followed by "Toba" (11,185 occurrences), "Karo" (6,714 occurrences), "suku" (3,241 occurrences), and "adat" (2,782 occurrences). This lexical distribution underscores how public discourse surrounding regional identities in multilingual environments can be tracked effectively via frequency metrics before being subjected to nuanced computational filtering.

Analysis of the Word Time Grid indicates that increases in the frequency of these keywords consistently align with surges in negative sentiment across the network, mobilized through central hashtags such as #kalak_karo (263 posts), #batak (255 posts), and #toba (219 posts). From the perspective of Social Identity Theory (SIT), the dominance of these terms represents not only a linguistic trend but also a concrete manifestation of Digital Political Labour (DPL). Users employ the terms "Batak" and "Karo" extensively and deliberately as mechanisms of othering, thereby reinforcing intergroup boundaries and perpetuating segregation within their respective echo chambers. This pattern mirrors how traditional identity structures and orally transmitted historical divisions migrate into unstructured digital spheres to actively delineate boundaries between "us" and "them" (Tajfel et al. 2001; Khairani and Wiradnyana 2023)

4.4. Social and Policy Implications

The empirical findings presented in this study offer critical insights that extend beyond structural network metrics and carry significant implications for digital policy and social cohesion in the Global South, particularly in multicultural societies such as Indonesia. The highly fragmented network structure (Modularity = 0.500979) and the prevalence of polarizing local-language expressions reveal a substantial structural vulnerability in the architecture's capacity for sub-national identity politics. For government regulatory bodies, including the Indonesian Ministry of Communication and Digital Affairs (Kementerian Komdigi), these results underscore the urgent need to move beyond generic, national-language (Indonesian) automated content moderation and to implement ethnolinguistically sensitive frameworks.

Standard algorithmic filters routinely fail to interpret localized micro-aggressions, irony, and "othering" narratives embedded in regional languages such as Karo or Batak slang. Generic lexicons and English-centric models often lack the contextual capability to capture domain-specific or identity-based hate speech. Consequently, policymakers are encouraged to collaborate with computational sociologists and local linguists to develop dynamic, region-specific lexicon databases. Such resources can more effectively monitor, detect, and mitigate digital hate speech before it escalates into offline communal conflict, in alignment with current calls for domain-adaptive natural language processing frameworks that preserve and understand localized ethnolinguistics.

This study identifies a harmful interaction between platform design and the amplification of primordial sentiments. The prominence of anonymous counterpublic accounts (e.g., @tanyakanrl and @tanyarlfees)

and hardline partisan actors as central information bridges demonstrates that Twitter/X's engagement-driven algorithms incentivize affective polarization (Charlton et al. 2016; Ahmed et al. 2024). By prioritizing high-emotion content to maximize user attention, the platform subsidizes digital political labor that undermines inter-group dialogue. Users become confined within algorithmic filter bubbles, continually producing content that validates their own group's sentiments while delegitimizing the out-group (Katsarou et al. 2021).

Consequently, there is a critical societal and ethical imperative to advance algorithmic accountability. Digital platforms in developing nations should be legally required to modify their recommendation engines, transitioning from engagement-centric metrics to algorithmic structures that deliberately promote cross-ideological and cross-ethnic interactions (H. Zhou et al. 2024). These structural and systematic reforms are essential to dismantle highly segregated echo chambers that dominate public discourse and threaten the long-term stability of democratic institutions (Kydros et al. 2021).

5. Conclusion

The digital manifestation of ethnic identity contestation in the Global South is examined through an analysis of the "Karo Bukan Batak" discourse on Twitter/X using an integrated computational social science framework. This approach combines macro-level Social Network Analysis (SNA) using NodeXL with micro-level Support Vector Machine (SVM) sentiment classification calibrated with a local-language lexicon, enabling empirical mapping of sub-national primordial politics in online spaces. Structural analysis identifies a highly fragmented digital ecosystem, as evidenced by an elevated modularity score (Modularity = 0.500979) and minimal density (0.000047), indicating that the discourse is dominated by 6,691 isolated echo chambers rather than a cohesive public sphere. Within these clusters, users engage in significant digital political labor to enforce rigid in-group boundaries and propagate narratives of othering, as demonstrated by the high predictive accuracy of the SVM model in isolating prevailing negative sentiments (F1-score = 0.90).

Integrating structural network positions with textual sentiments highlights significant social and policy implications for multicultural societies such as Indonesia. The strategic centrality of anonymous counterpublic arenas (e.g., @tanyakanrl and @tanyarlfs) and hardline partisan actors as primary information bridges demonstrates a harmful synergy between engagement-driven platform architectures and the amplification of affective polarization. As Twitter/X algorithms prioritize high-emotion content to maximize user attention, these mechanisms effectively subsidize conflict and enable younger generations to re-entrench historical ethnic stereotypes under the protection of anonymity.

Additionally, the prominence of the generative Artificial Intelligence account @grok as a major information bridge indicates a shifting paradigm in which automated non-human actors actively and often hazardously mediate ethnolinguistic disputes. These findings demonstrate that standard, national-language automated content moderation frameworks implemented by regulatory bodies such as the

Indonesian Ministry of Communication and Digital Affairs (Kementerian Komdigi) are fundamentally inadequate for interpreting localized microaggressions, irony, and regional slang.

In conclusion, this study finds that digital platforms are not passive channels for discourse distribution; rather, their architectures structurally exacerbate societal segregation. To safeguard social cohesion and democratic stability in ethnically diverse developing nations, there is an urgent need to adopt ethnolinguistically adaptive moderation frameworks and enforce legal requirements for algorithmic accountability, thereby shifting platform mechanics from engagement-centric metrics toward bridge-building recommendation engines.

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Figures

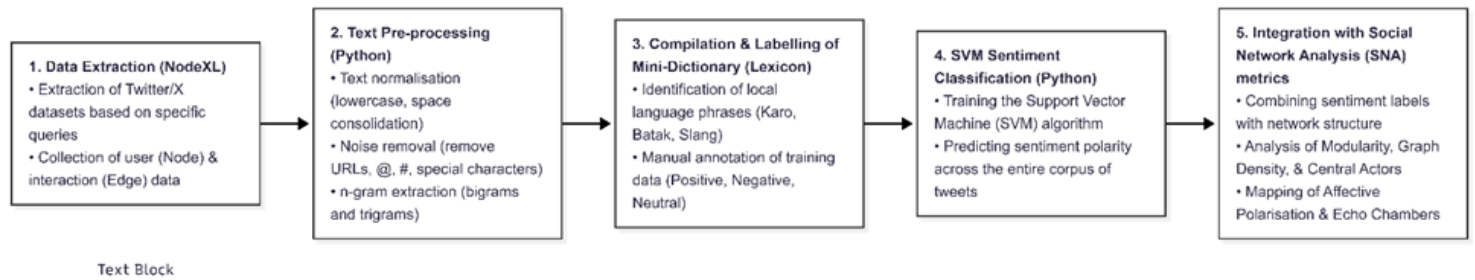


Figure 1

Research Workflow/Framework

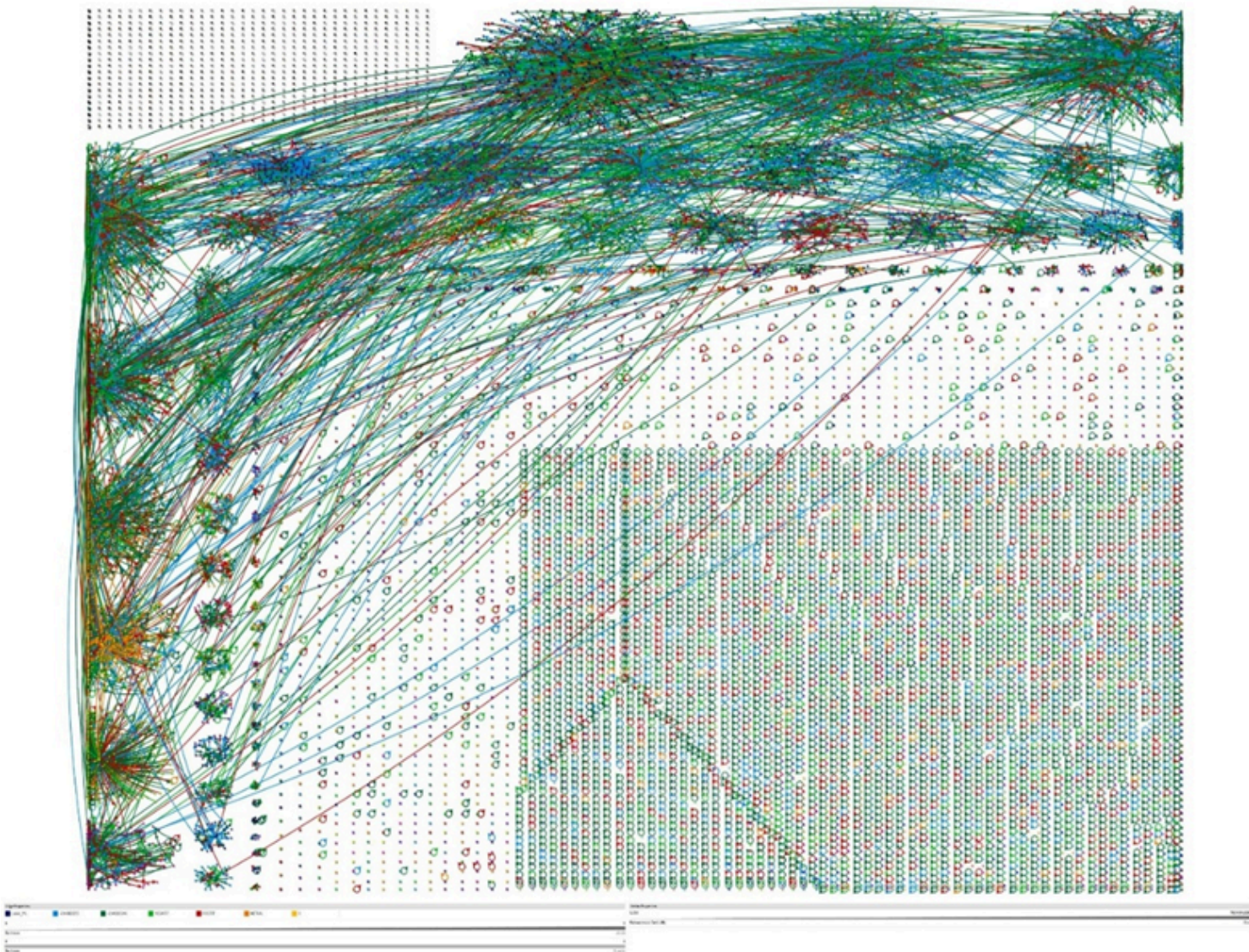


Figure 2

Sentiment Analysis Visualization Using Cleaned Python Data

Network Visualisation Map (Network Sociogram / Graph)

