OPEN ACCESS

https://doi.org/10.62159/dawuh.v7i2

DAWUH: Islamic Communication Journal Vol. 7 No. 2 (2026)

Research

Public Discourse on Waste Sorting Policy: A Sentiment and Topic Analysis

Ita Musfirowati Hanika*

Email : ita.mh@universitaspertamina.ac.id

Received: 15 June 2026	Revised: 29 June 2026	Accepted: 31 July 2026

Abstract

Waste-sorting policies require not only public participation but also effective communication and implementation support. This study examines public discourse surrounding Jakarta's waste-sorting policy through 413 YouTube comments by integrating IndoBERT and SentiStrength for sentiment analysis, Liu's framework for opinion-expression analysis, LDA for topic modeling, and human annotation for model validation. Negative sentiment dominated the discourse, with IndoBERT classifying 62.0% of comments as negative and demonstrating stronger agreement with human coders than SentiStrength. Most opinions were expressed through regular-direct structures and explicit expressions. LDA identified three major discussion topics: Waste Sorting Infrastructure and Collection Practices (37.8%), Government Performance and Policy Accountability (36.1%), and Waste Disposal Behavior and Environmental Awareness (26.2%). Negative sentiment was concentrated in discussions of infrastructure and collection practices (65.4%) and government performance and accountability (63.8%). By integrating transformer-based and lexicon-based sentiment analysis with opinion-expression analysis, topic modeling, and human validation, this study provides a more comprehensive understanding of public discourse than sentiment analysis alone. The findings indicate that negative sentiment reflects not only opposition to waste sorting but also concerns about institutional and operational barriers, highlighting the need for two-way policy communication that addresses citizens' feedback and implementation challenges.

Keywords: waste sorting policy; public discourse; sentiment analysis; indobert; sentistrength; topic modeling

INTRODUCTION

Waste has become a serious environmental and public health threat, particularly when inadequately managed or improperly disposed of. Improper waste disposal can contribute to land degradation and ecosystem disruption (Vaverková et al., 2019), contaminate water and soil (Bhat et al., 2022; Pernebayev & Aitimbetova, 2026), generate greenhouse gas emissions (Lou & Nair, 2009), and increase the risks of respiratory illnesses, infections, and vector-borne diseases among exposed communities (Purohit et al., 2026). These threats are expected to intensify as global municipal solid waste generation rises from 2.1 billion tonnes in 2023 to a projected 3.8 billion tonnes by 2050, while under a business-as-usual scenario, the proportion subjected to uncontrolled disposal is expected to increase from 38% in 2020 to 41% by 2050 (UNEP, 2024).

These challenges are especially pronounced in developing countries, where waste generation often outpaces population growth and economic development, placing increasing pressure on already constrained waste management systems. Municipal authorities face substantial financial burdens, high collection costs, and institutional, technical, and organizational constraints that hinder the effective functioning of waste management systems (Abarca Guerrero et al., 2013; Kumari & Raghubanshi, 2023).

Indonesia exemplifies these challenges at a critical scale. By the end of 2025, only 25% of the country's waste was adequately managed, leaving 75% at risk of environmental pollution (Ministry of Environment/Environmental Control Agency [KLH/BPLH], 2026), while only around 10% was sorted for recycling and resource recovery, largely through the informal sector (Regional Knowledge Centre for Marine Plastic Debris [RKC-MPD], 2025).

These challenges are particularly acute in Jakarta, Indonesia's largest metropolitan area, which generates approximately 7,700–8,000 tonnes of waste daily, with an estimated 55 million tonnes accumulated at the Bantargebang Integrated Waste Treatment Facility (TPST) (Jakarta Provincial Government, 2025). Nearly half of the city's waste consists of food waste (49.87%), followed by plastic (22.95%) and paper and cardboard (17.24%) (Dinas Lingkungan Hidup Provinsi DKI Jakarta, 2024), underscoring the need to move beyond the conventional collect–transport–dispose model towards waste reduction and separation at source.

In response to these challenges, the Jakarta Provincial Government issued Governor's Instruction No. 5 of 2026, requiring households, offices, and commercial areas to separate waste at source into four categories: organic, inorganic, hazardous and toxic (B3), and residual waste. The policy combines local monitoring and education with sanctions for non-compliance and incentives for successful implementation, and officially took effect on May 10, 2026 (Puspitasari, 2026).

However, the policy has generated diverse public responses. One concern is that it places disproportionate responsibility on citizens while providing insufficient oversight of industrial waste producers and leaving the role of informal waste pickers unclear within the new waste management system (Fundrika, 2026). While this criticism does not necessarily represent broader public opinion, it highlights the need for a systematic examination of how citizens perceive, evaluate, and express their responses to the policy.

Understanding these broader public responses requires evidence beyond individual statements reported in the news. Although surveys and interviews remain valuable approaches, they may be constrained by cost, scalability, and timeliness (Corbett & Savarimuthu, 2022). Social media provides a complementary source of naturally occurring public discourse, revealing how people interpret, evaluate, and discuss emerging policies as well as how viewpoints and controversies evolve through online interactions (Li et al., 2019).

The interactive and participatory nature of social media enables users not only to consume content but also to publicly express their views and interact with others (Gaenssle & Budzinski, 2021; Hu et al., 2017). On YouTube, user comments provide naturally occurring data that capture audience reactions, opinions, and interactions surrounding specific issues and policies, making them a valuable source for examining public discourse (Madden et al., 2013). As an influential platform with a large and diverse audience, YouTube has increasingly been used to investigate public discourse across various issues (Kim et al., 2024; Tsironis et al., 2024) and was therefore selected as the data source for this study.

To systematically examine these reactions, sentiment analysis, the computational process of identifying and categorizing opinions in text was employed to identify positive, negative, and neutral responses (Liu, 2012). This approach has been applied to environmental issues, including climate change, household waste segregation and recycling, and broader waste-related concerns (Jiang et al., 2021; Sham & Mohamed, 2022; Yuliansyah et al., 2024).

However, sentiment classification needs to account for contextual polarity, as the same word or expression may convey different sentiments depending on the context in which it appears (Wilson et al., 2009). Examining discussion topics alongside sentiment provides a more comprehensive understanding of the issues underlying public responses.

To capture such contextual variation in Indonesian-language comments, this study employed IndoBERT, a transformer-based language model developed for Indonesian natural language processing as part of the IndoLEM benchmark (Koto et al., 2020). Built on the BERT architecture and trained on large-scale Indonesian corpora, IndoBERT represents words in relation to their surrounding context, making it particularly relevant for sentiment classification in Indonesian-language discourse (Wilie et al., 2020). However, its classifications remain dependent on patterns learned from training data and may be less reliable when encountering informal expressions, domain-specific vocabulary, or linguistic patterns that differ from those represented during training.

To provide a complementary perspective, SentiStrength was employed as a lexicon-based approach that determines sentiment from the polarity and strength of sentiment-bearing words while accounting for linguistic cues such as negation, intensifiers, emoticons, and idiomatic expressions (Thelwall et al., 2010). Thus, the two approaches represent different mechanisms of sentiment classification: IndoBERT relies on contextual representations learned from data, whereas SentiStrength relies on lexical sentiment scores and linguistic rules. Comparing their outputs allows the study to examine where contextual and lexicon-based approaches converge or diverge in interpreting public responses.

To strengthen analytical robustness, the computational classifications were further triangulated with independent human annotations. Human judgments served as an additional interpretive reference rather than an absolute ground truth, enabling comparison across contextual, lexicon-based, and human interpretations of sentiment. This study contributes by integrating IndoBERT, SentiStrength, Liu's opinion framework, topic modeling, and human validation into a single analytical framework to examine sentiment, opinion expression, and discussion topics simultaneously. Accordingly, this study addresses two research questions: (1) What are the dominant sentiment patterns in YouTube comments on Jakarta's waste sorting policy? and (2) How do different types of sentiment expression manifest across topics in public discourse?

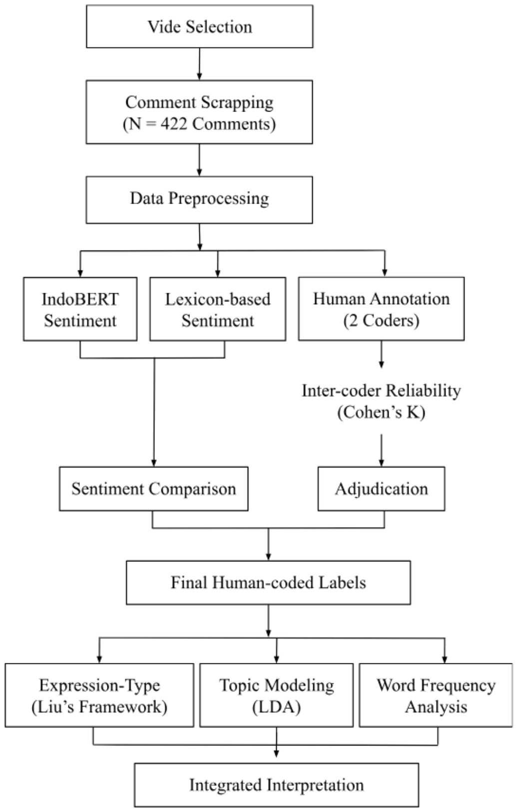
METHODS

This study examined public discourse surrounding Jakarta's 2026 waste separation policy using YouTube comments as naturally occurring data. A computational approach was combined with human annotation to capture multiple dimensions of public responses, including sentiment polarity, forms of sentiment expression, and dominant discourse topics. The methodological procedure comprised video selection and comment extraction, data preprocessing, automated and human-based classification, textual analysis, model evaluation, and integrated interpretation.

Research Design

This study employed a mixed-methods computational design to examine public discourse surrounding Jakarta's waste sorting policy. The unit of analysis was individual YouTube comments posted in response to news videos covering the policy. The research design integrated computational text analysis with independent human annotation to examine multiple dimensions of public discourse, including sentiment polarity, opinion structure, expression mode, and discourse topics. Figure 1 presents the overall analytical workflow, including data collection, preprocessing, computational analyses, human annotation, and integrated interpretation.

Figure 1. Overview of the research workflow



Following the analytical workflow presented in Figure 1, the computational analysis consisted of four complementary procedures. First, sentiment polarity was independently classified as positive, neutral, or negative using IndoBERT and SentiStrength, representing transformer-based contextual and lexicon-based approaches, respectively. Second, following Liu's framework (2012), comments were classified according to opinion structure and expression mode. Third, Latent Dirichlet Allocation (LDA) was applied to identify latent discourse topics across the corpus. Finally, word-frequency analysis was conducted within each sentiment category to identify recurring lexical patterns associated with different evaluative orientations.

In parallel, two independent coders annotated all comments without access to the computational predictions. Human annotation served as an independent validation and interpretive layer rather than the primary source of classification. Inter-coder reliability was assessed using Cohen's Kappa to evaluate the consistency of human judgments. Comments on which the coders disagreed were subsequently reviewed through an adjudication process to produce a final set of human-coded labels. These final annotations were used as the reference for evaluating the sentiment classifications generated by IndoBERT and the domain-adapted lexicon-based classifier. Human-coded thematic categories additionally provided interpretive support for understanding the substantive concerns represented in the computationally identified discourse patterns.

The analytical outputs were subsequently integrated to examine dominant sentiment orientations in public responses, the relationships between sentiment polarity, opinion structure, and expression mode, and the substantive issues characterizing public discourse surrounding Jakarta's waste sorting policy.

Data Collection and Sampling

Using the YouTube Data API v3, comments and video metadata, including video ID, title, channel, publication date, view count, and comment count, were collected from Indonesian news channels covering Jakarta's waste sorting policy. Data collection was restricted to May 4–12, 2026, capturing immediate public responses surrounding three key policy milestones: the signing of the Governor's Instruction on May 4, the official declaration of the Waste Sorting Movement on May 10, and the beginning of policy implementation on May 11.

Videos were purposively selected based on four inclusion criteria: (1) publication within the specified period; (2) at least 500 views; (3) at least three comments; and (4) direct relevance to the waste sorting policy or closely related waste-management issues. The minimum thresholds of 500 views and three comments were adopted to ensure that the selected videos had received sufficient audience exposure and generated observable public engagement, as views and comments are commonly used as indicators of user engagement in social media research (Aldous et al., 2019). Government-owned channels were excluded to focus on public discourse within independent news media environments. Based on these criteria, 36 videos from 13 news channels were included, yielding an initial corpus of 422 raw comments.

Following data cleaning, nine unusable comments were excluded, resulting in a final analytical corpus of 413 comments. All 413 comments were subjected to computational analysis using IndoBERT, SentiStrength, and Liu's framework opinion classification, and were independently annotated by two human coders. This common analytical corpus enabled direct comparison between computational classifications and human annotations.

Table 1. Dataset Characteristics

Item	Description
Data Source	Indonesian news channels on YouTube (YouTube Data API v3)
Collection period	May 4–12, 2026
Policy milestones captured	(1) Signing of the Governor's Instruction (May 4); (2) Official declaration of the Waste Sorting Movement (May 10); (3) Start of policy implementation (May 11)
Sampling criteria	Published within the target period; minimum 500 views; minimum 3 comments; directly addressed the waste sorting policy or closely related waste-management issues
Channels included	13 news channels
Videos included & Comments	36 videos, 422 raw comments, 413 final corpus

Data Preprocessing

Because each analytical method required a different form of text, several text representations were retained. Raw comments were preserved for human annotation and lexicon-based sentiment analysis to retain informal expressions, negation, intensifiers, and other cues relevant to sentiment. A normalized version was used for IndoBERT and the classification of opinion structure and expression mode, while a further processed version was prepared for topic modeling and word-frequency analysis.

The initial dataset contained 422 raw comments. Text normalization included case folding, Unicode normalization, removal of URLs, user mentions, hashtag symbols, and non-informative characters, as well as normalization of 47 common Indonesian slang terms (e.g., *gak* → *tidak* and *udah* → *sudah*). Negation words such as *tidak*, *bukan*, and *jangan*, as well as contrastive conjunctions such as *tapi*, *namun*, and *padahal*, were retained because they can affect the meaning and orientation of an opinion (Liu, 2012). Eight comments containing no usable text, such as emoji- or URL-only entries, and one timestamp-only comment ("1:03") were excluded, resulting in a final corpus of 413 comments. Different text representations were then prepared to support the computational analyses performed in this study, as summarized in Table 2.

Table 2. Text preprocessing and text representations used in the study

Step	Output/ Text Representation	Description	Used for Analysis
1	**Raw comments**	Original YouTube comments after data collection	Corpus documentation
2	**Normalized text**	Case folding, Unicode normalization, slang normalization, removal of URLs, mentions, hashtags, and non-informative characters while retaining negation and contrastive conjunctions	IndoBERT sentiment classification
3	**Cleaned text**	Tokenization, stopword removal, and lemmatization/stemming (except words required for sentiment analysis)	Topic modeling (LDA)
4	**Lexicon-refined text**	Domain-specific lexical refinement by excluding non-evaluative policy terms from sentiment scoring	SentiStrength sentiment classification
5	**Final analytical corpus**	413 valid comments after preprocessing	Opinion structure analysis (Liu's framework), agreement analysis, and topic–sentiment analysis

For topic modeling and word-frequency analysis, the normalized text underwent additional stopword removal and domain-specific normalization. Meaningful multiword expressions were combined into bigrams, such as *pilah_sampah*, *tempat_sampah*, *bank_sampah*, and *tanggung_jawab*. Stemming was not applied because preliminary inspection showed that it could alter the meaning of Indonesian words and reduce interpretability; for example, *setuju* could become *tuju* and *ternyata* could become *nyata*.

For SentiStrength, domain-specific lexical refinement was applied during sentiment scoring. Waste-related terms such as *sampah*, *limbah*, *organik*, *pemilahan*, and *pengelolaan* were treated as neutral when they functioned only as topic-related vocabulary. These words were not removed from the comments but were prevented from contributing to polarity scores, reducing the risk that domain-specific vocabulary would be incorrectly interpreted as positive or negative sentiment.

Development Tools and Techniques

All computational analyses were conducted in Python 3.14.3 within a Jupyter Notebook environment. Data processing was performed using pandas (v2.3.1) and NumPy (v2.3.2). Sentiment classification employed the Hugging Face Transformers library (v4.55.0) with PyTorch (v2.8.0) using the pre-trained IndoBERT sentiment model *ayameRushia/bert-base-indonesian-1.5G-sentiment-analysis-smsa*. The lexicon-based sentiment classifier was implemented through custom Python functions using the Indonesian SentiStrength-ID lexical resources (Masdevid, 2015) together with additional linguistic rules. Topic modeling, text vectorization, and model evaluation were implemented using scikit-learn (v1.7.1). Indonesian-language preprocessing was supported by

Sastrawi (v1.0.1), while graphical outputs were generated using Matplotlib (v3.10.5) and WordCloud (v1.9.4). All analytical procedures were implemented through reproducible Python scripts and applied consistently to the final corpus of 413 comments.

Sentiment Polarity Classification

Sentiment polarity was operationalized into three categories: positive, negative, and neutral. Positive sentiment referred to comments expressing favorable evaluations, such as praise, approval, support, satisfaction, or optimism, whereas negative sentiment included unfavorable evaluations, such as criticism, rejection, dissatisfaction, anger, or opposition. Neutral sentiment referred to comments that did not show a clear positive or negative evaluation, including factual or descriptive statements and subjective statements without a clear evaluative orientation (Wiebe et al., 1999; Pozzi et al., 2016). Thus, neutrality was not limited to purely objective statements, as a comment could express a personal view or assumption without conveying either positive or negative polarity.

Sentiment polarity was then classified using two complementary approaches to compare contextual and lexicon-based methods for Indonesian social media discourse. The first approach used IndoBERT (model: *ayameRushia/bert-base-indonesian-1.5G-sentiment-analysis-smsa*), based on the Indonesian BERT architecture trained on large-scale Indonesian text (Wilie et al., 2020). Each normalized comment was classified as positive, neutral, or negative, accompanied by a confidence score indicating the model's prediction certainty.

The second approach employed a lexicon-based classifier using the Indonesian SentiStrength-ID lexicon (Masdevid, 2015). Sentiment polarity was determined by aggregating the scores of sentiment-bearing words while accounting for linguistic features such as negation, booster words, emoticons, idiomatic expressions, and contrastive conjunctions. Sentiment expressed after contrastive conjunctions (e.g., *tapi*, *tetapi*, and *namun*) was assigned greater interpretive weight. The resulting polarity scores were constrained to the standard SentiStrength range of −5 to +5 and subsequently mapped into three sentiment categories: positive, neutral, and negative.

To improve classification accuracy in the policy context, the classifier incorporated the domain-specific lexical refinement described in the preprocessing stage. Topic-descriptive terms that did not convey evaluative meaning were excluded from sentiment scoring to reduce domain lexical bias (Liu, 2012; Thelwall et al., 2010).

Both IndoBERT and SentiStrength therefore produced comparable three-class sentiment labels. Rather than treating one approach as the reference standard, their outputs were compared to examine areas of agreement and disagreement between contextual and lexicon-based sentiment classification. Model performance was subsequently evaluated against independent human annotations.

Expression-Type Classification

To complement sentiment polarity analysis, each comment was further examined based on opinion structure and expression mode, which capture how opinions are constructed and communicated rather than their positive, negative, or neutral orientation. While sentiment polarity identifies the evaluative direction of a comment, these dimensions provide additional insight into the linguistic and pragmatic forms through which public responses toward Jakarta's waste sorting policy are articulated.

Following Liu's (2012) framework, opinion structure was classified into two main categories: regular opinion and comparative opinion. Regular opinions were further differentiated into direct and indirect opinions. A direct opinion explicitly evaluates an entity or one of its aspects, whereas an indirect opinion conveys an evaluation through the effects or consequences of an entity on another entity or condition. A comparative opinion, in contrast, expresses similarities, differences, or preferences between two or more entities, situations, or alternatives based on a shared aspect (Jindal & Liu, 2006a, 2006b; Liu, 2006, 2011, 2012).

Independently from opinion structure, comments were also classified according to their expression mode as either explicit or implicit. An explicit opinion is a subjective statement that directly expresses a regular or comparative opinion, whereas an implicit opinion is an ostensibly objective statement that implies an evaluation through a desirable or undesirable fact or situation (Liu, 2012). Thus, opinion structure and expression mode represent distinct but complementary dimensions: a comment may, for example, constitute a regular–direct explicit opinion, a regular–indirect implicit opinion, or a comparative explicit opinion.

This two-dimensional classification was applied to the full corpus of 413 comments, allowing the analysis to examine not only the distribution of opinion structures and expression modes but also how these forms intersected with sentiment polarity identified by IndoBERT and SentiStrength.

Human Annotation, Reliability, and Triangulation

To provide an independent interpretive reference for the computational analyses, two human coders independently annotated all 413 comments. The coders worked without access to each other's annotations or to the outputs generated by IndoBERT and SentiStrength. For the present analysis, human annotations were used for two dimensions: sentiment polarity (Positive, Neutral, or Negative) and thematic category, representing the substantive issue or concern addressed in each comment.

The annotation process followed a standardized codebook containing operational definitions and decision rules for sentiment classification. Positive sentiment represented favorable evaluations such as praise, approval, support, or optimism; negative sentiment represented unfavorable evaluations such as criticism, rejection, dissatisfaction, or opposition; and neutral sentiment referred to comments without a clear positive or negative evaluative orientation. Coders were instructed to interpret each comment as a complete utterance and to consider contextual cues such as negation, contrast, and implied evaluation rather than relying solely on individual sentiment-bearing words.

Inter-rater reliability was assessed using Cohen's Kappa (κ), with percentage agreement calculated as a supplementary measure (Landis & Koch, 1977). Reliability was assessed separately for sentiment polarity and thematic categorization. The resulting reliability statistics are reported in the Results section. Because no adjudication procedure was conducted, disagreements between coders were retained rather than combined into a single consensus label.

Human annotation served as an independent validation and interpretive layer within the methodological triangulation. Human sentiment judgments were used to assess the extent to which the classifications produced by IndoBERT and SentiStrength converged with human interpretation, while the manually identified thematic categories supported the interpretation of substantive issues within the discourse. Separately, opinion structure (Regular–Direct, Regular–Indirect, and Comparative) and expression mode (Explicit and Implicit) were examined computationally using Liu's framework (2012) and cross-tabulated with the sentiment classifications produced by IndoBERT and SentiStrength. Together, these approaches enabled comparison across computational sentiment methods, linguistic forms of opinion expression, and human interpretation without treating any single method as an absolute ground truth.

Topic Modeling and Word-Frequency Analysis

Topic modeling was conducted to identify recurring themes in public discussions surrounding Jakarta's waste sorting policy. Latent Dirichlet Allocation (LDA) was used as an exploratory unsupervised method to identify groups of words that frequently co-occurred across comments (Blei et al., 2003). Unlike the thematic categories derived from human coding, LDA did not rely on predefined categories, allowing latent patterns to emerge directly from the corpus.

LDA was applied to the processed text representation described in the preprocessing stage, which included stopword removal, domain-specific normalization, and the construction of meaningful bigrams such as *pilah_sampah*, *bank_sampah*, and *tanggung_jawab*. Stemming was not applied to preserve the semantic meaning and interpretability of Indonesian words.

The number of topics was determined empirically rather than specified in advance. LDA models containing two to ten topics were compared using topic coherence and perplexity. Greater emphasis was placed on coherence because the objective was to identify substantively interpretable themes rather than solely optimize statistical fit (Röder et al., 2015; Maier et al., 2021). The final model was selected by considering both model performance and the interpretability of the resulting topics. Each topic was then labelled based on its most representative terms and the comments with the highest topic probabilities.

Each comment was assigned to its dominant topic, defined as the topic with the highest membership probability. Topic assignments were subsequently cross-tabulated with sentiment classifications to examine whether sentiment orientations differed across substantive areas of discussion. This allowed the analysis to identify not only whether public responses were positive, neutral, or negative, but also which policy issues were associated with these sentiments.

Finally, word-frequency analysis was used to identify recurring terms within positive, neutral, and negative comments, with word clouds serving only as supplementary visualizations. LDA, word-frequency analysis, and human thematic coding were treated as complementary approaches: LDA identified latent patterns in the corpus, word frequencies highlighted recurring lexical features, and human coding provided contextual interpretation of the substantive issues discussed.

Model Evaluation and Integrated Analysis

Model evaluation was conducted on the 413 comments included in both the computational and human annotation datasets. IndoBERT and SentiStrength were evaluated against the independent human sentiment annotations using accuracy, precision, recall, weighted F1-score, and Cohen's Kappa. Because no adjudication was conducted to produce a single consensus label, model performance was assessed against the two coders' annotations separately. Inter-coder agreement was also examined to provide context for interpreting the model–human agreement and the inherent variability of human sentiment judgments.

Agreement between IndoBERT and SentiStrength was additionally examined to assess convergence between contextual and lexicon-based sentiment classification. Cases in which the two approaches produced different polarity labels were examined qualitatively to identify potential sources of disagreement, including negation, implicit evaluation, contrastive expressions, and domain-specific vocabulary. Model outputs were also cross-tabulated with opinion structure (Regular–Direct, Regular–Indirect, and Comparative) and expression mode (Explicit and Implicit) to examine whether classification patterns differed according to how opinions were structured and communicated.

Finally, the analytical outputs were integrated to provide a multidimensional account of public responses to Jakarta's waste sorting policy. Sentiment analysis identified the evaluative orientation of responses; Liu-based classification captured opinion structure and expression mode; LDA identified recurring discourse topics; and human thematic coding provided contextual interpretation of the substantive issues discussed. Cross-tabulation across these dimensions was used to examine relationships among sentiment, opinion structure, expression mode, and discourse topics. This integration enabled the study to examine not only whether public responses were positive, neutral, or negative, but also how opinions were expressed, which policy issues they concerned, and where computational and human interpretations converged or diverged.

RESULTS AND DISCUSSION

This section presents and discusses the findings from 413 YouTube comments concerning Jakarta's waste sorting policy. The analysis examines sentiment polarity using IndoBERT and SentiStrength, followed by their inter-method comparison, opinion structure and expression mode, and the main discourse topics identified through topic modeling and thematic analysis. Computational sentiment classifications are further compared with human annotations. Together, these analyses reveal what sentiments dominated the discussion, how these opinions were expressed, and which policy issues shaped public responses.

Corpus Characteristics and Public Engagement

The final corpus comprised 413 comments from 36 videos published by 13 Indonesian news channels. Table 2 summarizes their distribution across the five channels contributing the most comments, with the remaining channels grouped as *Other Channels*, and includes comment likes as a descriptive indicator of engagement with individual responses. These characteristics provide context for the subsequent analysis by showing how public discussion and interaction were distributed across the selected news channels.

Table 3. Distribution of Comments and Comment Engagement by News Channel

News Channel	Number of Videos	Number of Comments	Percentage of Comments (%)	Total Comment Likes	Average Likes per Comment
Metro TV	12	103	24.9	95	0.92
CNN Indonesia	3	65	15.7	30	0.46
Liputan 6	2	47	11.4	16	0.34
Warta Kota Production	6	47	11.4	35	0.74
Harian Kompas	1	39	9.4	40	1.03
Other Channels (8)	12	112	27.1	43	0.38
Total	**36**	**413**	**100.0**	**259**	**0.63**

As shown in Table 3, Metro TV contributed the largest number of comments (103; 24.9%) and received the highest total comment likes (95). However, a higher volume of comments did not necessarily correspond to higher engagement per comment. Harian Kompas, despite contributing only one video and 39 comments, recorded the highest average likes per comment (1.03), followed by Metro TV (0.92). Overall, the 413 comments received 259 likes, averaging 0.63 likes per comment. These patterns suggest that the volume of discussion and engagement with individual comments varied across news channels.

Temporal Trends in Public Sentiment

Examining the temporal distribution of comments provides context for understanding when public discussion intensified during the policy period. Rather than treating the 413 comments as a single aggregate corpus, daily comment volume was examined in relation to key policy milestones to determine whether public attention developed gradually or was concentrated around particular events.

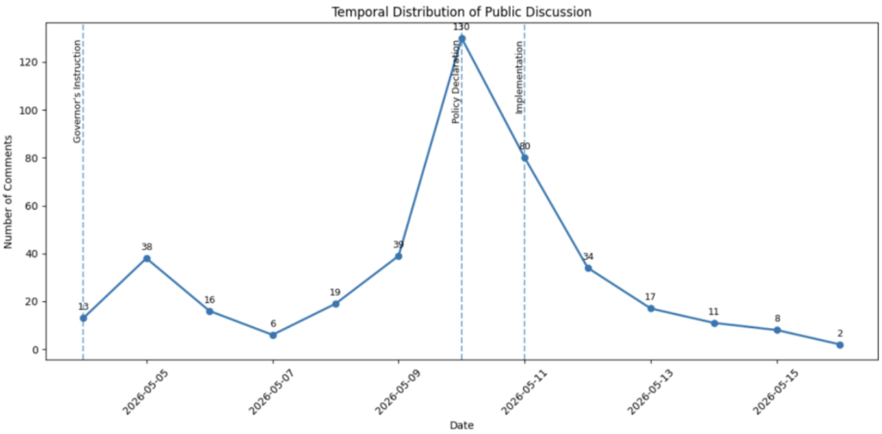


Figure 2. Daily Distribution of Comments

Figure 2 reveals a clear event-centered pattern of public discussion. Comment activity remained relatively limited following the Governor's Instruction on May 4 before increasing sharply on May 10, coinciding with the official declaration of the Waste Sorting Movement, when approximately 130 comments were recorded. However, the beginning of implementation on May 11 did not generate a second peak; instead, comment activity declined rapidly thereafter. This pattern suggests a short-lived attention cycle centered primarily on the policy declaration, which generated substantially greater discussion than either the initial instruction or the implementation stage.

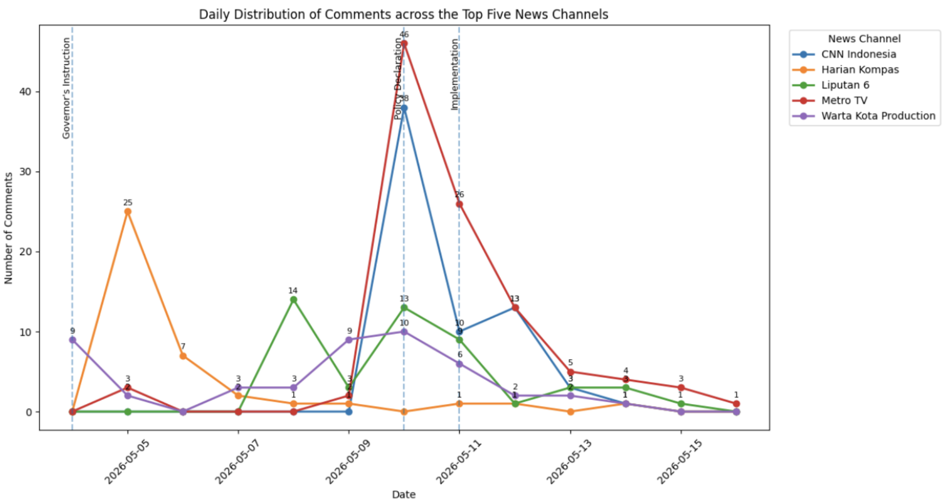


Figure 3. Daily Comment Distribution across the Five Most Active News Channels

Figure 3 further shows that the temporal distribution of comments varied across news channels. The May 10 surge was concentrated primarily in Metro TV and CNN Indonesia, which recorded 46 and 38 comments, respectively, accounting for 84 comments on that day. Other channels displayed different temporal patterns. Harian Kompas reached its highest activity earlier, with 25 comments on May 5, while Liputan 6 peaked on May 8 with 14 comments. Warta Kota Production showed a more dispersed pattern, with smaller increases across several dates. These variations indicate that the overall temporal pattern was not uniformly distributed across news channels, but was shaped by distinct channel-specific discussion cycles.

Sentiment Polarity

Sentiment polarity was examined using both IndoBERT and SentiStrength to determine whether contextual and lexicon-based approaches produced comparable interpretations of public responses.

Table 4. Overall Sentiment Distribution Based on IndoBERT and SentiStrength

Sentiment	IndoBERT	SentiStrength	Difference
Negative	256 (62.0%)	210 (50.8%)	11.2 pp
Neutral	87 (21.1%)	106 (25.7%)	−4.6 pp
Positive	70 (16.9%)	97 (23.5%)	−6.6 pp
Total	413	413	

As shown in Table 4, the two methods produced broadly similar patterns, although IndoBERT identified a higher proportion of negative comments (62.0%) than SentiStrength (50.8%), a difference of 11.2 percentage points. Conversely, SentiStrength classified slightly more comments as neutral (25.7% vs. 21.1%) and positive (23.5% vs. 16.9%), indicating differences in how the two approaches interpret sentiment polarity.

Agreement and Disagreement between IndoBERT and SentiStrength

Given the differences in sentiment distributions produced by IndoBERT and SentiStrength, the level of agreement between the two approaches was examined to determine how consistently they classified the same comments. Agreement refers to cases in which both methods assigned the same sentiment label, whereas disagreement refers to cases in which the labels differed. Cross-classification and Cohen’s Kappa were used to assess the extent and pattern of agreement between the two methods.

Table 5. Agreement & Disagreement between IndoBERT and SentiStrength

IndoBERT	SentiStrength Negative	SentiStrength Neutral	SentiStrength Positive	Total
Negative	167 (65.2%)	50 (19.5%)	39 (15.2%)	256
Neutral	31 (35.6%)	41 (47.1%)	15 (17.2%)	87
Positive	12 (17.1%)	15 (21.4%)	43 (61.4%)	70
Total	210	106	97	413

Note. Percentages are calculated within IndoBERT sentiment categories (row percentages). Overall agreement = 60.8% (251/413); disagreement = 39.2% (162/413); Cohen’s $\kappa = 0.336$.

As shown in Table 5, IndoBERT and SentiStrength assigned the same sentiment label to 251 of 413 comments (60.8%), while 162 comments (39.2%) received different classifications. The overall Cohen’s Kappa was 0.336, indicating relatively limited agreement between the two methods beyond chance. Agreement was highest for comments classified as negative by IndoBERT, with 167 of 256 (65.2%) also classified as negative by SentiStrength, followed by positive comments, with 43 of 70 (61.4%) receiving the same label. Neutral sentiment showed the lowest agreement, with only 41 of 87 comments (47.1%) classified as neutral by both methods. Among IndoBERT-negative comments, 50 (19.5%) were classified as neutral and 39 (15.2%) as positive by SentiStrength, highlighting differences in how the two approaches interpreted the same expressions.

Human Validation of Sentiment Classification

Given the observed disagreement between IndoBERT and SentiStrength, human-coded sentiment labels were used as an independent reference to evaluate how closely each computational approach aligned with human interpretation. IndoBERT and SentiStrength classifications were separately compared with the human annotations using accuracy, precision, recall, weighted F1-score, and Cohen's Kappa. This comparison was intended to assess relative alignment with human interpretation rather than to treat human coding as an infallible ground truth.

Table 6. Model Performance against Human-Coded Sentiment

Comparison	Accuracy	Weighted Precision	Weighted Recall	Weighted F1	Cohen's κ
IndoBERT vs Coder 1	0.690	0.691	0.690	0.688	0.447
IndoBERT vs Coder 2	0.678	0.698	0.678	0.679	0.425
SentiStrength vs Coder 1	0.530	0.556	0.530	0.541	0.219
SentiStrength vs Coder 2	0.557	0.596	0.557	0.571	0.263

Note. N = 413 comments for all comparisons. Weighted metrics were used to account for differences in class distribution.

Human validation showed that IndoBERT aligned more closely with both coders than SentiStrength across all evaluation metrics (Table 6). IndoBERT achieved accuracies of 0.690 and 0.678 against Coder 1 and Coder 2, respectively, with weighted F1-scores of 0.688 and 0.679. Its Cohen's Kappa values were also higher ($\kappa = 0.447$ and 0.425) than those obtained by SentiStrength ($\kappa = 0.219$ and 0.263). SentiStrength achieved lower accuracies of 0.530 and 0.557 and weighted F1-scores of 0.541 and 0.571. The consistency of this pattern across both human coders indicates that IndoBERT showed stronger alignment with human interpretation of sentiment in the corpus. These results suggest that contextual language modelling is better suited to Indonesian social media discourse, where sentiment is often conveyed through contextual meaning rather than explicit evaluative words. Consequently, IndoBERT was able to approximate human judgment more closely than the lexicon-based SentiStrength approach.

Expression Mode based on Liu's Framework

To further examine how sentiment was expressed in the comments, the corpus was analyzed using Liu's framework, distinguishing opinion structure into regular-direct, regular-indirect, and comparative forms, as well as expression mode into explicit and implicit expressions. These categories were subsequently cross-tabulated with IndoBERT and SentiStrength classifications to examine whether sentiment patterns varied according to how opinions were linguistically expressed.

Table 7. Opinion Structure based on Liu's Framework

Opinion Structure	N	% Corpus	Indo BERT Negative	Indo BERT Neutral	Indo BERT Positive	Senti Strength Negative	Senti Strength Neutral	Senti Strength Positive
Regular Direct	268	64,9%	56,0%	25,7%	18,3%	44,4%	32,5%	23,1%
Regular Indirect	36	8,7%	83,3%	8,3%	8,3%	66,7%	11,1%	22,2%
Compar-ative	109	26,4%	69,7%	13,8%	16,5%	61,5%	13,8%	24,8%
Total	413	100,0%	—	—	—	—	—	—

Regular-direct expressions constituted the dominant opinion structure, accounting for 268 comments (64.9%), followed by comparative expressions (26.4%) and regular-indirect expressions (8.7%). Negative sentiment predominated across all three structures in both methods, but was particularly pronounced among regular-indirect expressions, classified as negative in 83.3% of cases by IndoBERT and 66.7% by SentiStrength. Comparative expressions also showed substantial negativity, although IndoBERT again produced a higher negative proportion (69.7%) than SentiStrength (61.5%). The largest difference occurred among regular-direct expressions, where IndoBERT classified 56.0% as negative compared with 44.4% by SentiStrength.

To further assess the consistency between the two sentiment analysis methods, model agreement was examined across the three opinion structures. This analysis indicates whether the level of agreement between IndoBERT and SentiStrength varied depending on how opinions were structured.

Table 8. Agreement between IndoBERT and SentiStrength by Opinion Structure

Opinion Type	N	Agreement_N	Agreement_%	Disagreement_N	Disagreement_%
Comparative	109	69	63.3	40	36.7
Direct	268	159	59.3	109	40.7
Indirect	36	23	63.9	13	36.1

As shown in Table 8, despite differences in sentiment distributions, model agreement remained relatively consistent across opinion structures, ranging from 59.3% for direct expressions to 63.9% for indirect expressions. This indicates that disagreement between IndoBERT and SentiStrength was not concentrated within a particular opinion structure.

In addition to opinion structure, expression mode was examined to distinguish between explicit and implicit expressions.

Table 9. Expression Mode based on Liu's Framework

Expression Mode	N	% Corpus	Indo BERT Negative	Indo BERT Neutral	Indo BERT Positive	Senti Strength Negative	Senti Strength Neutral	Senti Strength Positive
Explicit	396	95,9%	60,9%	21,5%	17,7%	50,0%	26,5%	23,5%
Implicit	17	4,1%	88,2%	11,8%	0,0%	70,6%	5,9%	23,5%
Total	413	100,0%	—	—	—	—	—	—

Explicit expressions dominated the corpus, accounting for 396 comments (95.9%), whereas only 17 comments (4.1%) were classified as implicit. Across both expression types, IndoBERT identified a higher proportion of negative sentiment than SentiStrength. Negative sentiment was particularly pronounced among implicit expressions, although this finding should be interpreted cautiously given the small number of implicit comments (n = 17). The predominance of explicit expressions suggests that YouTube users generally communicated their evaluations openly rather than relying on indirect or implicit language, making the platform a valuable source for examining citizens' policy perceptions and concerns.

Table 10. Expression Mode's Model Agreement

Expression Mode	N	Agreement_N	Agreement%	Disagreement_N	Disagreement%
Explicit	396	240	60.6	156	39.4
Implicit	17	11	64.7	6	35.3

Model agreement was also examined across expression modes to determine whether explicit and implicit expressions produced different levels of consistency between the two methods. Agreement was relatively similar across the two modes, reaching 60.6% for explicit expressions and 64.7% for implicit expressions. This suggests that model disagreement was not concentrated in implicit expressions, although the small number of implicit comments limits further interpretation.

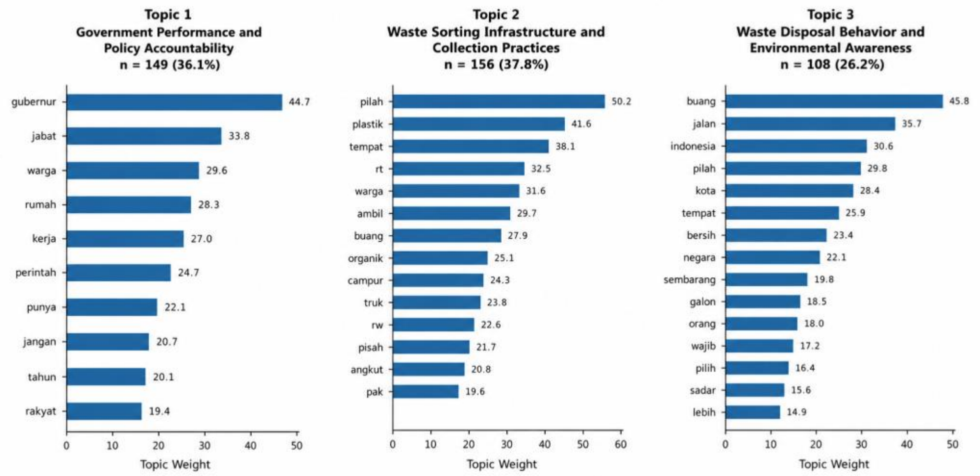
Topics of Public Discourse

Prior to topic modeling, domain-specific stopwords were removed to reduce the influence of highly frequent but weakly discriminative terms, such as *sampah*, *Jakarta*, and *DKI*. These terms were common across the corpus but provided limited information for distinguishing one topic from another. Terms with greater substantive relevance to particular issues, such as *pilah*, *truk*, *RT/RW*, *gubernur*, and *warga*, were retained.

To determine the optimal number of topics, LDA models with two to eight topics (K = 2–8) were evaluated. Model selection was based on NPMI coherence, which measures the semantic consistency of words within each topic, and perplexity, which evaluates the model's statistical fit to the corpus. These metrics were complemented by substantive interpretability and parsimony, ensuring that the selected solution produced conceptually distinct and meaningful topics without unnecessary fragmentation.

The evaluation did not identify a single model that performed best across all criteria. Although the eight-topic solution achieved the highest NPMI coherence score (0.214), it was also associated with substantially higher perplexity and produced topics that became increasingly fragmented and conceptually overlapping. In contrast, the three-topic solution achieved a good balance between semantic coherence (0.175), statistical fit (perplexity = 978.84), and interpretability. Examination of the highest-weighted terms together with representative comments showed that the three topics captured distinct and meaningful dimensions of public discourse while avoiding unnecessary thematic fragmentation. Following the principle of parsimony, the three-topic solution (K = 3) was therefore selected for subsequent analysis.

Table 11. Topic Modeling of Public Discourse



Note. The figure shows the top 14–15 terms with the highest weights in each topic. Topic weights represent the relative importance of each term within a topic.

The final model identified Waste Sorting Infrastructure and Collection Practices as the largest topic (n = 156; 37.8%), followed closely by Government Performance and Policy Accountability (n = 149; 36.1%). The third topic, Waste Disposal Behavior and Environmental Awareness, accounted for 108 comments (26.2%). Together, these findings indicate that public discourse extended beyond the act of waste sorting itself to encompass the operational capacity required to implement the policy, government accountability, and citizens' environmental behavior. This suggests that public discussion focused not only on the policy objective but also on the practical and institutional conditions necessary for its successful implementation.

To further examine how public evaluations varied across these substantive areas, the three topics were subsequently cross-tabulated with IndoBERT sentiment classifications. IndoBERT was selected because it demonstrated stronger agreement with human coders in the validation analysis. This approach made it possible to identify whether negative sentiment was distributed evenly across the identified topics or concentrated in particular aspects of the policy. The results showed that negative sentiment was most prevalent in discussions of Waste Sorting Infrastructure and Collection Practices (65.4%)**,** followed by Government Performance and Policy Accountability (63.8%)**,** whereas Waste Disposal Behavior and Environmental Awareness exhibited a comparatively lower proportion of negative sentiment (54.6%).

Table 12. IndoBERT Sentiment Distribution across LDA Topics

Topic	Negative	Neutral	Positive	Total
Government Performance and Policy Accountability	95 (63.8%)	31 (20.8%)	23 (15.4%)	149
Waste Sorting Infrastructure and Collection Practices	102 (65.4%)	31 (19.9%)	23 (14.7%)	156

Waste Disposal Behavior and Environmental Awareness	59 (54.6%)	25 (23.1%)	24 (22.2%)	108
Total	**256 (62.0%)**	**87 (21.1%)**	**70 (16.9%)**	**413**

Negative sentiment predominated across all three topics, but was most pronounced in discussions of Waste Sorting Infrastructure and Collection Practices (65.4%), followed by Government Performance and Policy Accountability (63.8%). In contrast, Waste Disposal Behavior and Environmental Awareness showed a lower proportion of negative sentiment (54.6%) and the highest proportion of positive sentiment (22.2%). These findings suggest that public criticism was directed primarily toward the implementation and institutional aspects of the policy rather than the concept of waste sorting itself.

To illustrate the discourse underlying each LDA topic, representative comments were selected from each topic–sentiment combination. Comments with the highest topic probabilities were chosen because they most strongly reflected the semantic characteristics of their assigned topic. Table 13 presents these examples to complement the quantitative findings by illustrating how citizens expressed criticism, support, and neutral evaluations within each of the three discourse topics.

Table 13. Representative Comments by LDA Topic and Sentiment

Topic	Sentiment	Probability	Representative Comment
1: Government Performance and Policy Accountability	Negative	0.993	“Ide bagus😂jangan focus hanya kepada sampah rumah tangga, seharusnya yang sangat urgent dan perlu disadari oleh kita semua dan mulai digalakkan buat rakyat sekarang kita harus belajar dan terus belajar untuk cerdas kedepannya supaya bisa memilah dalam memilih mana pemimpin/pejabat yang bukan hanya menjadi "sampah"...”
1: Government Performance and Policy Accountability	Neutral	0.996	“Kalau gue jadi gubernur jakarta. Tanggul laut itu yang bertanggung jawab pihak pengelola properti yang di pinggir laut….”
1: Government Performance and Policy Accountability	Positive	0.947	“Pemulung: Terimakasih Pak Gub dan masyarakat DKI JAKARTA…”
2: Waste Sorting Infrastructure and Collection Practices	Negative	0.992	“Dari zaman rikiplik pun kami sudah memilah antara sampah organik untuk masuk tong kompos kami di halaman, sampah dapur "non recycleable" alias yang gak diambil pemulung (walaupun itu kantong plastik makanan)...”
2: Waste Sorting Infrastructure and Collection Practices	Neutral	0.983	“Buat aturan misalnya hari senin hanya mengangkut sampah basah kalau ada sampah kering tidak diangkut, libatkan RT/RW…”

2: Waste Sorting Infrastructure and Collection Practices.	Positive	0.987	"Kami betul2 senang sekali kalau Jakarta akan menjadi kota yg. bersih, kota hijau, nyaman untuk semua penduduknya…"
3: Waste Disposal Behavior and Environmental Awareness	Negative	0.979	"Seumur hidup sbagai manusia dewasa, gw sdh melakukan pilah pilah sampah domestik sendiri... Orang Indonesia masih payah kesadaran soal keberhasilan. Padahal katanya kebersihan sebagian dari iman..."
3: Waste Disposal Behavior and Environmental Awareness	Neutral	0.995	"Saran untuk warga Jakarta untuk membuat komposter sederhana…"
3: Waste Disposal Behavior and Environmental Awareness	Positive	0.969	"bagus nih, harusnya diikuti diseluruh kota-kota…"

Note. Representative comments are reproduced in their original Indonesian language for analytical purposes. Usernames and other personally identifiable information, where present, have been removed to protect user privacy. Ellipses (...) indicate that non-essential portions of comments have been omitted for brevity.

As shown in Table 13, each topic contained negative, neutral, and positive responses, indicating that citizens expressed diverse evaluations within the same policy issue. Taken together with the topic-level sentiment distribution, these representative comments suggest that negative sentiment was directed less toward the principle of waste sorting itself than toward concerns about government performance, waste-management infrastructure, and the practical challenges of policy implementation. At the same time, positive comments reflected support for the policy goal, while neutral comments often provided suggestions or observations regarding its implementation.

Discussion

The findings show that negative sentiment dominated public discourse on the waste-sorting policy, although IndoBERT and SentiStrength differed in how they classified public responses. The moderate level of agreement between the two models (κ = 0.336) indicates that the choice of sentiment analysis approach can substantially influence the interpretation of online public opinion. Human validation further demonstrated that IndoBERT aligned more closely with both human coders, suggesting that contextual language models are better suited to capturing the evaluative meaning of informal Indonesian social media comments. This finding highlights the importance of contextual understanding in sentiment analysis, particularly in policy-related discussions where opinions are often expressed through conversational language, incomplete sentences, or subtle evaluative cues rather than explicit sentiment words.

The analysis based on Liu's framework provides further insight into how these evaluations were communicated. Most comments employed regular-direct opinion structures and explicit expressions, indicating that citizens generally conveyed their views openly rather than indirectly. Nevertheless, disagreement between IndoBERT and SentiStrength remained relatively consistent across regular-direct, regular-indirect, comparative, explicit, and implicit expressions. This suggests that differences between contextual and lexicon-based approaches are not primarily determined by the structural form of an opinion, but rather by their ability to interpret contextual meaning and evaluative intent. In other words, online public discourse often communicates criticism, suggestions, comparisons, and expectations through linguistic contexts that extend beyond the presence of individual sentiment-bearing words, reinforcing the value of contextual language models for analyzing policy-related discussions.

These findings can be further understood through the Situational Theory of Publics (STP), which explains how people's communication behavior is shaped by how they recognize a problem and perceive constraints in responding to it (Grunig & Hunt, 1984). Its later development also identifies problem recognition and constraint recognition as important factors shaping communicative action (Kim & Grunig, 2011). In this study, the predominance of negative sentiment does not necessarily indicate rejection of waste sorting. Citizens may recognize waste as an important problem while also identifying barriers that make the expected behavior difficult to perform. This interpretation is supported by the higher proportion of negative sentiment in discussions of Waste Sorting Infrastructure and Collection Practices (65.4%) and Government Performance and Policy Accountability (63.8%), compared with Waste Disposal Behavior and Environmental Awareness (54.6%). Comments about sorting facilities, waste collection, institutional responsibilities, and government readiness can therefore be interpreted as indications of perceived practical and institutional constraints. Rather than rejecting the policy itself, many comments questioned whether the institutional capacity and supporting infrastructure were sufficient to enable the behavioral changes expected from citizens.

From a communication perspective, this pattern suggests that waste-sorting communication should address both *problem recognition* and *constraint recognition*. Messages that simply encourage citizens to sort their waste may be insufficient when citizens perceive that infrastructure or collection systems do not support the requested behavior. This is particularly relevant because recent research on waste-sorting policies on social media has also treated online responses as an important source for understanding public feedback toward policy communication. Environmental communication should therefore combine messages about individual responsibility with clear information about available infrastructure, collection procedures, institutional responsibilities, and policy follow-through. Social media comments can serve as valuable public feedback by revealing gaps between policy messages, implementation capacity, and citizens' expectations, allowing policy communication to become more responsive to the barriers experienced or perceived by the public (Heaselgrave & Denyer-Simmons, 2016; Zhang & Lu, 2025).

CONCLUSION

This study demonstrates that public responses to waste-sorting policy cannot be fully understood through sentiment polarity alone. By integrating sentiment analysis, opinion-expression analysis based on Liu's framework, and topic modeling, the study shows that online public discourse reflects not only citizens' attitudes toward the policy but also their evaluations of government performance, implementation capacity, and public responsibility. This integrated approach provides a more comprehensive understanding of how environmental policies are interpreted and discussed in digital spaces.

The findings also have important implications for environmental policy communication. Negative sentiment should not be interpreted simply as public opposition to waste sorting, but rather as feedback that highlights perceived implementation barriers and unmet public expectations. Policy communication is therefore likely to be more effective when it combines persuasive messages encouraging behavioral change with clear information about supporting infrastructure, institutional responsibilities, and implementation processes. In this way, social media can serve as an important channel for identifying communication gaps and strengthening two-way interaction between governments and citizens.

Finally, this study contributes methodologically by demonstrating the value of combining contextual sentiment analysis with opinion-expression analysis and topic modeling to examine online public discourse. Rather than relying solely on sentiment polarity, this approach captures both how opinions are expressed and what issues they address, providing richer insights for communication research and evidence-based policymaking. Future research could extend this framework to other social media platforms, policy domains, and longitudinal datasets to examine how public discourse evolves throughout different stages of policy implementation.

AI-Assistance Declaration

The authors confirm that AI-assisted tools (ChatGPT, OpenAI) were used solely to support language refinement, grammar improvement, manuscript organization, and the development of Python scripts for data processing and visualization. All intellectual contributions, including the research conception, study design, data collection, pre-processing decisions, analytical framework, coding procedures, interpretation of findings, theoretical discussion, and conclusions were conceived, conducted, and critically evaluated by the authors. AI-generated outputs were reviewed, verified, and substantially edited before inclusion in the manuscript. The authors accept full responsibility for the accuracy, integrity, originality, and final content of this work.

REFERENCES

Abarca Guerrero, L., Maas, G., & Hogland, W. (2013). Solid waste management challenges for cities in developing countries. *Waste Management, 33*(1), 220–232. https://doi.org/10.1016/j.wasman.2012.09.008

Aldous, K. K., An, J., & Jansen, B. J. (2019). View, like, comment, post: Analyzing user engagement by topic at four levels across five social media platforms for 53 news organizations. *Proceedings of the International AAAI Conference on Web and Social Media, 13*(1), 47–57. https://doi.org/10.1609/icwsm.v13i01.3208

Badan Pusat Statistik Provinsi DKI Jakarta. (2023). *Volume sampah yang terangkut per hari menurut jenis sampah di Provinsi DKI Jakarta (ton), 2022*. https://jakarta.bps.go.id/id/statistics-table/2/OTE2IzI=/volume-sampah-yang-terangkut-per-hari-menurut-jenis-sampah-di-provinsi-dki-jakarta.html

Bhat, R. A., Singh, D. V., Qadri, H., Dar, G. H., Dervash, M. A., Bhat, S. A., Unal, B. T., Ozturk, M., Hakeem, K. R., & Yousaf, B. (2022). Vulnerability of municipal solid waste: An emerging threat to aquatic ecosystems. *Chemosphere, 287*, 132223. https://doi.org/10.1016/j.chemosphere.2021.132223

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet allocation. *Journal of Machine Learning Research, 3*, 993–1022.

Budzinski, O., Gaenssle, S., & Lindstädt-Dreusicke, N. (2021). The battle of YouTube, TV and Netflix: An empirical analysis of competition in audiovisual media markets. *SN Business & Economics, 1*(9), Article 122. https://doi.org/10.1007/s43546-021-00122-0

Chen, L., Huang, L., Ma, W., Ma, S., & Li, Y. (2025). The study on the dissemination of waste sorting policies on social media and the public's feedback attitudes: A text analysis based on comment data of policies in 46 key cities in China. *Frontiers in Environmental Science, 13*, Article 1632996. https://doi.org/10.3389/fenvs.2025.1632996

Corbett, J., & Savarimuthu, B. T. R. (2022). From tweets to insights: A social media analysis of the emotion discourse of sustainable energy in the United States. *Energy Research & Social Science, 89*, 102515. https://doi.org/10.1016/j.erss.2022.102515

DevelopmentAid. (2026). *World waste: Statistics by country and brief facts*. https://www.developmentaid.org/news-stream/post/158158/world-waste-statistics-by-country

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human*

Language Technologies (NAACL-HLT 2019), 1, 4171–4186. https://doi.org/10.18653/v1/N19-1423
Dinas Lingkungan Hidup Provinsi DKI Jakarta. (n.d.). *Dashboard persampahan*. https://silika.jakarta.go.id/dashboard_persampahan
Dinas Lingkungan Hidup Provinsi DKI Jakarta. (2024, November 28). *Sisa makanan menjadi penyumbang komposisi sampah terbesar di DKI Jakarta* [Instagram post]. Instagram. https://www.instagram.com/p/DC6DRKmSeLX/
Fundrika, B. A. (2026, May 18). *Aturan pilah sampah DKI dikritik, mengapa beban lebih banyak ke warga? Suara.com*. https://www.suara.com/news/2026/05/18/111117/aturan-pilah-sampah-dki-dikritik-mengapa-beban-lebih-banyak-ke-warga
Giganti, P., Errichiello, G., & Falcone, P. M. (2025). Exploring public discourse on green hydrogen via YouTube comments: A comparative sentiment analysis using VADER and ChatGPT. *Economic Analysis and Policy, 88*, 2012–2030. https://doi.org/10.1016/j.eap.2025.11.014
Grunig, J. E., & Hunt, T. (1984). *Managing public relations*. Holt, Rinehart and Winston.
Heaselgrave, F., & Denyer-Simmons, P. (2016). Culture, competency and policy: Why social media dialogue is limited in Australian local government. *Journal of Communication Management, 20*(2), 133–147. https://doi.org/10.1108/JCOM-07-2015-0059
Hu, S., Gu, J., Liu, H., & Huang, Q. (2017). The moderating role of social media usage in the relationship among multicultural experiences, cultural intelligence, and individual creativity. *Information Technology & People, 30*(2), 265–281. https://doi.org/10.1108/ITP-04-2016-0099
Jiang, P., Zhou, J., Fan, Y. V., Klemeš, J. J., Zheng, M., & Varbanov, P. S. (2021). Data analysis of resident engagement and sentiments in social media enables better household waste segregation and recycling. *Journal of Cleaner Production, 319*, 128809. https://doi.org/10.1016/j.jclepro.2021.128809
Kementerian Lingkungan Hidup/Badan Pengendalian Lingkungan Hidup. (2026). *Rakornas pengelolaan sampah 2026: Menteri LH tegaskan transformasi total tata kelola sampah nasional*. https://kemenlh.go.id/news/detail/rakornas-pengelolaan-sampah-2026-menteri-lh-tegaskan-transformasi-total-tata-kelola-sampah-nasional
Kim, H.-S., Pak, J., Chung, M.-Y., & Kim, Y. (2024). How self-disclosure builds cancer communities through authentic stories on YouTube: Mediating role of user participation in self-disclosure reciprocity. *Computers in Human Behavior, 156*, 108226. https://doi.org/10.1016/j.chb.2024.108226
Kim, J.-N., & Grunig, J. E. (2011). Problem solving and communicative action: A situational theory of problem solving. *Journal of Communication, 61*(1), 120–149. https://doi.org/10.1111/j.1460-2466.2010.01529.x
Koto, F., Rahimi, A., Lau, J. H., & Baldwin, T. (2020). IndoLEM and IndoBERT: A benchmark dataset and pre-trained language model for Indonesian NLP. *Proceedings of the 28th International Conference on Computational Linguistics*, 757–770. https://doi.org/10.18653/v1/2020.coling-main.66
Kumari, T., & Raghubanshi, A. S. (2023). Waste management practices in the developing nations: Challenges and opportunities. In P. Singh, P. Verma, R. Singh, A. Ahamad, & A. C. S. Batalhão (Eds.), *Waste management and resource recycling in the developing world* (pp. 773–797). Elsevier. https://doi.org/10.1016/B978-0-323-90463-6.00017-8
Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics, 33*(1), 159–174. https://doi.org/10.2307/2529310
Li, R., Crowe, J., Leifer, D., Zou, L., & Schoof, J. (2019). Beyond big data: Social media challenges and opportunities for understanding social perception of energy. *Energy Research & Social Science, 56*, 101217. https://doi.org/10.1016/j.erss.2019.101217
Liu, B. (2012). *Sentiment analysis and opinion mining*. Morgan & Claypool Publishers. https://doi.org/10.2200/S00416ED1V01Y201204HLT016

Lou, X. F., & Nair, J. (2009). The impact of landfilling and composting on greenhouse gas emissions—A review. *Bioresource Technology, 100*(16), 3792–3798. https://doi.org/10.1016/j.biortech.2008.12.006

Madden, A., Ruthven, I., & McMenemy, D. (2013). A classification scheme for content analyses of YouTube video comments. *Journal of Documentation, 69*(5), 693–714. https://doi.org/10.1108/JD-06-2012-0078

Maier, D., Waldherr, A., Miltner, P., Wiedemann, G., Niekler, A., Keinert, A., Pfetsch, B., Heyer, G., Reber, U., Häussler, T., Schmid-Petri, H., & Adam, S. (2018). Applying LDA topic modeling in communication research: Toward a valid and reliable methodology. *Communication Methods and Measures, 12*(2–3), 93–118. https://doi.org/10.1080/19312458.2018.1430754

Masdevid. (2015). *SentiStrength-ID: Sentiment strength detection in Bahasa Indonesia* [Software]. GitHub. https://github.com/masdevid/sentistrength_id

Pemerintah Provinsi DKI Jakarta. (2025). *Gubernur Pramono sambut kolaborasi pengelolaan sampah bersama Keuskupan Agung Jakarta*. https://www.jakarta.go.id/siaran-pers/6005-SP-HMS-10-2025

Pernebayev, Z., & Aitimbetova, A. (2026). Environmental impacts of municipal solid waste disposal in urban areas: A systematic review of contamination pathways, assessment methods, and mitigation strategies. *Sustainability, 18*(8), 3900. https://doi.org/10.3390/su18083900

Pozzi, F. A., Fersini, E., Messina, E., & Liu, B. (Eds.). (2016). *Sentiment analysis in social networks*. Morgan Kaufmann.

Purohit, H., Pandya, V., & Chauhan, M. (2026). Impact of waste management on public health and environmental sustainability. *EPJ Web of Conferences, 348*, 01022. https://doi.org/10.1051/epjconf/202634801022

Puspitasari, D. (2026, May 7). *Pramono: Program pilah sampah di Jakarta dimulai Minggu 10 Mei*. *detikNews*. https://news.detik.com/berita/d-8478378/pramono-program-pilah-sampah-di-jakarta-dimulai-minggu-10-mei

Regional Knowledge Centre for Marine Plastic Debris. (2025). *Indonesia's plastic problem: Why sorting waste must come before recycling*. https://rkcmpd-eria.org/news/indonesia-s-plastic-problem-why-sorting-waste-must-come-before-recycling

Röder, M., Both, A., & Hinneburg, A. (2015). Exploring the space of topic coherence measures. *Proceedings of the Eighth ACM International Conference on Web Search and Data Mining*, 399–408. https://doi.org/10.1145/2684822.2685324

Sham, N. M., & Mohamed, A. (2022). Climate change sentiment analysis using lexicon, machine learning and hybrid approaches. *Sustainability, 14*(8), 4723. https://doi.org/10.3390/su14084723

Thelwall, M., Buckley, K., Paltoglou, G., Cai, D., & Kappas, A. (2010). Sentiment strength detection in short informal text. *Journal of the American Society for Information Science and Technology, 61*(12), 2544–2558. https://doi.org/10.1002/asi.21416

Tsironis, G., Daglis, T., & Tsagarakis, K. P. (2024). The circular economy through the prism of machine learning and the YouTube video media platform. *Journal of Environmental Management, 370*, 121977. https://doi.org/10.1016/j.jenvman.2024.121977

United Nations Environment Programme. (2024). *Global waste management outlook 2024: Beyond an age of waste—Turning rubbish into a resource*. https://www.unep.org/resources/global-waste-management-outlook-2024

Vaverková, M. D., Maxianová, A., Winkler, J., Adamcová, D., & Podlasek, A. (2019). Environmental consequences and the role of illegal waste dumps and their impact on land degradation. *Land Use Policy, 89*, 104234. https://doi.org/10.1016/j.landusepol.2019.104234

Wiebe, J. M., Bruce, R. F., & O'Hara, T. P. (1999). Development and use of a gold-standard data set for subjectivity classifications. *Proceedings of the 37th Annual Meeting of the Association for Computational Linguistics*, 246–253. https://doi.org/10.3115/1034678.1034721

Wilie, B., Vincentio, K., Winata, G. I., Cahyawijaya, S., Li, X., Lim, Z. Y., Soleman, S., Mahendra, R., Fung, P., Bahar, S. Y., & Purwarianti, A. (2020). IndoNLU: Benchmark and resources for evaluating Indonesian natural language understanding. *Proceedings of the 1st Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 10th International Joint Conference on Natural Language Processing*, 843–857. https://aclanthology.org/2020.aacl-main.85/

Wilson, T., Wiebe, J., & Hoffmann, P. (2009). Recognizing contextual polarity: An exploration of features for phrase-level sentiment analysis. *Computational Linguistics, 35*(3), 399–433. https://doi.org/10.1162/coli.08-012-R1-06-90

Yuliansyah, H., Mulasari, S. A., Sulistyawati, Ghozali, F. A., & Sudarsono, B. (2024). Sentiment analysis of the waste problem based on YouTube comments using VADER and Deep Translator. *Jurnal Media Informatika Budidarma, 8*(1), 663–673. https://doi.org/10.30865/mib.v8i1.6918

Zhang, X., & Lu, F. (2025). Enhancing public health policy communication through government–citizen social media interactions: The impact of replying agents, inquiry tone, and institutional trust. *Policy & Internet, 17*(1), e70000. https://doi.org/10.1002/poi3.70000