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Public Sentiment on Indonesia's Free Nutritious Meal Program: A Mixed-Methods NLP Evaluation

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ABSTRACT

Large-scale nutrition intervention programs such as the Free Nutritious Meal Program (MBG) are likely to attract considerable attention on social media. While conventional evaluation techniques are often too slow to capture rapidly shifting sentiment, this study seeks to determine how sentiment can be evaluated. More specifically, we aimed to identify the key emerging issues. Methodology: In this study, one approach to examining emerging issues is to use a two-stage workflow in Natural Language Processing (NLP). The first step in sentiment analysis is using a transformer model (Indo-RoBERTa) to assign 'Positive', 'Negative', or 'Neutral' to 3,459 public texts from X (Twitter) social media. Secondly, we focused on 1,130 'Negative' texts. We used topic modeling (BERTopic) on this and identified the most critical clusters of issues to map and their relative importance. Results & Conclusions: Negative sentiment involves multiple factors, to which our model successfully highlighted four of the most impactful areas: (1) Financial concerns and budgetary priorities; (2) Responses to particular media coverage (e.g., Kompas); (3) Political general discourse; and (4) Expectations of particular local issues (education issues in Papua). Conclusion: Compared with the gaps in the program's nutrition components, the economic consequences, budget gaps, inequities, and regional policy deficiencies drew more public interest. Implications: The findings point to a clear need for a differentiated and open approach to communicating public policy. This approach should communicate the nutritional value and the need to align messaging with the public for the geographic and budgetary realities.

Key Messages:

- The NLP methods (Sentiment Analysis and BERTopic) perform well in assessing nutrition intervention policies in real Time.
- The primary concerns regarding the MBG program are not nutrition but rather budget issues, media influence, and geographic inequity.
- Policymakers need to communicate in a way that is budget-transparent and regionally adaptable to improve public buy-in.

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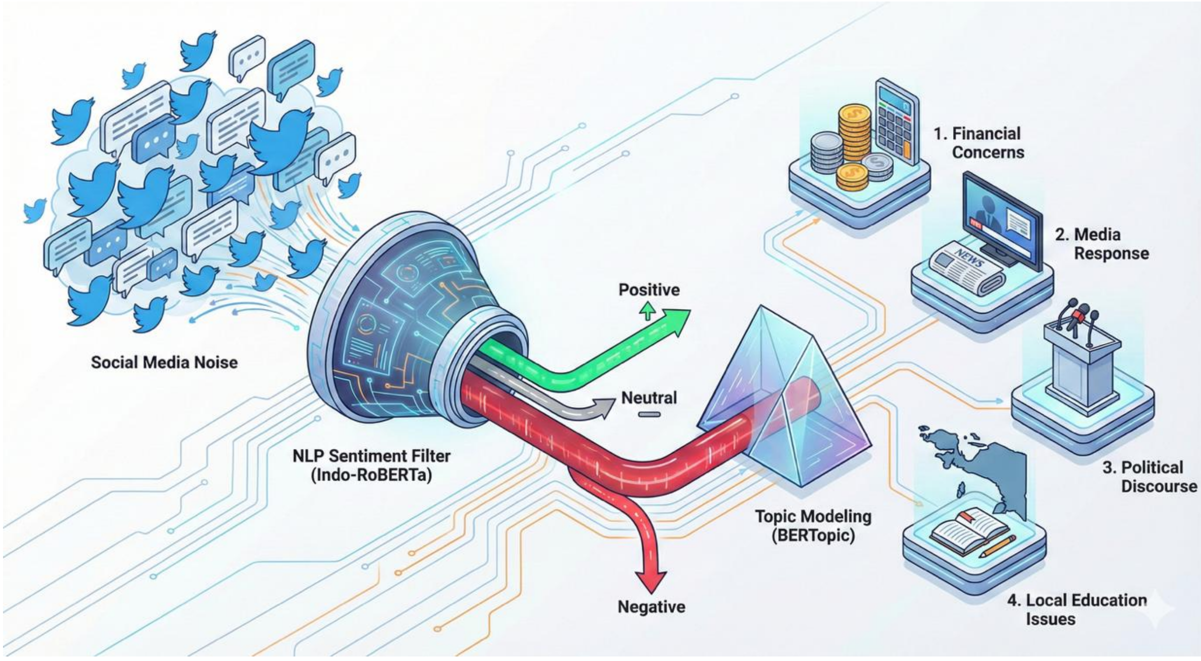
GRAPHICAL ABSTRACT



INTRODUCTION

Nutrition programs designed for children and adolescents form the basis for the development of human capital (1,2). As an example, the United States' "Food is Medicine" initiative highlights how integrating nutritional services into healthcare systems can shape public perceptions of health outcomes (3). In Indonesia, the Free Nutritious Meal (MBG) program represents a paradigm shift in national policy, transitioning focus from physical infrastructure to the development of human capital (1). Targeting approximately 82.9 million beneficiaries, including schoolchildren and pregnant women, this ambitious initiative aims to address persistent malnutrition issues, specifically supporting the national target of reducing stunting prevalence to 14% (1,2,4).

However, the implementation of such large-scale public policies faces significant challenges in securing public buy-in. The MBG program has sparked widespread discussion across digital social networks, driven by concerns over its massive fiscal implications—estimated at IDR 71 trillion (approx. USD 4.5 billion) for its first year—and the potential burden on the state budget deficit (1). Furthermore, early communication regarding the program has been described as equivocal, creating ambiguity about menu standards and budget allocation that risks generating negative sentiment (4). Parents have also expressed skepticism regarding hygiene, potential corruption, and the quality of meals provided (5).

Public perception of a program directly affects its acceptability (6,7). In multiple nations, studies show that public support for various food policies is influenced primarily by the framing of the issue and the proposed solution (8–10). Given the complexity of the MBG program, there is a significant risk of a communication gap between the public and policymakers (11,12). In this regard, the mass media acts as a critical bridge in shaping narratives and legitimizing policy decisions (13).

In this light, public and media discussion serves as an important resource for situation analysis, providing feedback, expectations, and criticisms of a program. While policy portfolios often rely on methods like surveys, these traditional approaches take time, incur high costs, and may lag behind rapidly shifting public opinion (14). NLP Text Mining offers an efficient, systematic, and evaluative approach to real-time policy tracking, capable of capturing nuanced public concerns that traditional methods might miss (14,15). From a consumer/public perspective, identifying gaps in information is crucial for bridging the divide for policy adoption and identifying shifts in communication strategy (11). Analyzing social media has proven valuable for understanding public narratives during policy design, as seen in nutrition labeling cases in Uruguay (16). However, the majority of work in this area has historically focused on fundamental

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sentiment analysis (positive, negative, neutral). This study argues that reliance on a simple 'negative' label is insufficient for decision-making without further deconstruction. We posit that negative sentiment specifically warrants granular analysis because, unlike positive sentiment which is often generic, negative feedback contains actionable diagnostic information regarding policy friction points. Negative discourse serves as a critical signal of implementation failures, such as the "equivocal communication" regarding budgets identified by Sianturi (4) or the structural anxieties regarding fiscal sustainability highlighted by Thawley (1). Therefore, decomposing these negative narratives is essential to uncover the specific "why" behind public resistance and provide the diagnostic evidence required for policy improvement (16,17).

METHODS

This study employs an analytical observational design with a computational mixed-methods approach, integrating quantitative and qualitative (NLP) techniques. The data employed consists of public discourse from the social media platform X (formerly Twitter) regarding the "Free Nutritious Meal" program. Raw data was collected using the X API with purposive sampling, utilizing search keywords such as "makan bergizi gratis," "program prabowo," and related variations. The dataset was scraped on February 11, 2025 (available at: https://www.kaggle.com/datasets/hanif281103/sentimen-publik-terhadap-makan-bergizi-gratis), spanning the period from January 8, 2025, to February 10, 2025. The initial corpus yields 3,459 raw records (DatasetMBG.csv) containing 15 variables, including temporal data (created_at), interaction metrics (favorite_count, retweet_count, reply_count), and user metadata (username, location). For the purpose of this study, the analysis primarily focused on the full_text column, which contains the unstructured textual arguments required for NLP analysis. Additionally, the created_at variable was utilized to ensure temporal validity.

Data Analysis Pipeline Data analysis was conducted through a structured NLP pipeline implemented in Python, comprising preprocessing, sentiment classification, and topic modeling. The following are the stages:

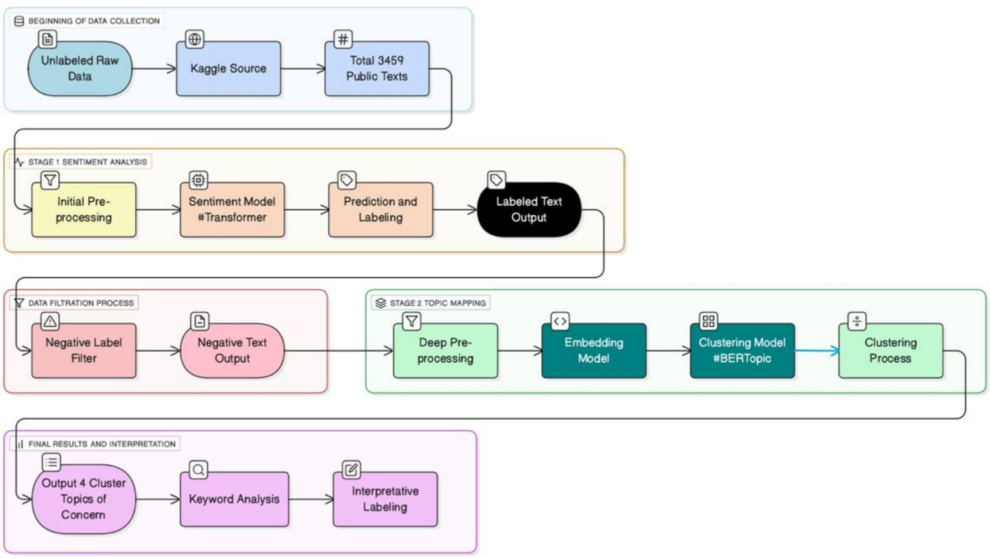

Figure 1. Method Analysis Sentiment

Data Preprocessing Pipeline

To ensure scientific reproducibility, the text preprocessing workflow utilized standard libraries tailored for Indonesian natural language processing. The raw text data underwent a multi-stage cleaning process utilizing the Python re (Regular Expression) library to remove noise, including URLs, user mentions (e.g., @username), and special characters. To address the informal nature of social media discourse, a custom slang normalization dictionary was employed to map non-standard terms to their formal equivalents (e.g., expanding 'mbg' to 'makan bergizi gratis' and 'gak' to 'tidak'). Furthermore, linguistic normalization was conducted using the Sastrawi library (v1.0.1). Specifically, we utilized Sastrawi's StopWordRemover to eliminate high-frequency but semantically low-value words and the

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Stemmer to reduce inflected words to their root forms, thereby reducing dimensionality and enhancing the semantic accuracy of the analysis.

Stage 1: Sentiment Analysis (Data Labeling)

The raw dataset (n=3,459) lacked pre-existing sentiment labels. To address this, we applied a transformer-based model, Indo-RoBERTa (w11wo/indonesian-roberta-base-sentiment-classifier), which is optimized for Indonesian social media text. Transformer architectures like RoBERTa are superior at detecting nuanced discourse compared to traditional machine learning models (15). This model processed each text and assigned a label of 'Positive', 'Negative', or 'Neutral', generating a labeled dataset (sentiment.csv).

Model Validation

To validate the model's performance in the specific context of the MBG program, a manual validation step was conducted on a random sample of 100 tweets. The model's predictions were compared against human-labeled ground truth, achieving an Accuracy of 89% and an F1-Score of 88%, confirming its reliability.

Data Filtration & Selection for Topic Modeling

In the data filtration phase for Stage 2, texts classified as 'Positive' and 'Neutral' were systematically excluded. This exclusion was justified by the study's primary objective to diagnose potential policy barriers and public concerns. While positive feedback typically reinforces existing successful implementations, negative discourse contains the granular, actionable diagnostic information required for substantive policy improvement. This focused approach aligns with complaint analysis frameworks in public policy research, allowing for a deeper semantic analysis of critical issues while optimizing computational resources. Consequently, only texts classified as 'Negative' with a confidence score exceeding 0.70 were retained for topic modeling (n=1,130) to ensure high analytical relevance and data quality.

Stage 2: Concern Topic Modeling (BERTopic)

The isolated corpus of negative texts was analyzed using BERTopic to extract latent themes. We configured the algorithm specifically for short, informal Indonesian text using the paraphrase-multilingual-MiniLM-L12-v2 embedding model, which converts documents into 384-dimensional vectors optimized for multilingual contexts. This methodology has proven effective in similar studies for extracting narratives from social media discourse (16) and identifying systemic gaps in health policies (12).

To ensure a data-driven discovery process, we utilized automatic topic selection (nr_topics="auto") rather than imposing a fixed number of clusters. This allowed the HDBSCAN algorithm to identify dense regions in the embedding space naturally. We set the minimum topic size (min_topic_size) to 10 to effectively filter out noise while retaining statistically significant thematic groups. Consequently, the emergence of the four final clusters was fundamentally data-driven. By allowing HDBSCAN to identify natural groupings based on semantic density, the model ensured that the clusters reflected genuine semantic coherence in public complaints. Finally, we applied hierarchical topic reduction to merge the initial micro-clusters into the four dominant themes presented in the results.

RESULTS

In Stage 1, 3,459 texts were reviewed for all analyses. Public opinion on the MBG programme was categorised into three sentiment categories: Negative, Positive, or Neutral. The Negative sentiment category had the most texts, comprising 1,130, while the Positive category had 1,061 texts, and Neutral had 1,268 texts. Consequently, the subsequent thematic analysis focused exclusively on the corpus of Negative texts (n=1,130).

Concern Topic Mapping

The BERTopic analysis identified four distinct themes of negative sentiment, as detailed in Table 1. Each cluster is characterized by specific keywords and representative discourse. Topic 0 represents the most dominant concern regarding budgetary constraints, where the public questions the source of funding and potential trade-offs with other sectors. Topic 1 shifts the focus to political skepticism, viewing the program as a tool for image-building by the new administration rather than a genuine health intervention.

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Furthermore, Topic 2 captures critical reactions toward media coverage (specifically mentioning 'Kompas'), reflecting public dissatisfaction with how budget cuts were framed in the news. Finally, Topic 3 highlights a significant center-periphery disconnect, specifically in Papua, where the public prioritizes educational infrastructure over the free meal program itself.

Table 1. Topic Mapping Results of Negative Sentiment Towards the MBG Program

Topic ID	Topic Label	Translated Keywords (Top 5)	Translated Representative Tweet
0	Budgetary Concerns & Policy Prioritization	eat, free, budget (*anggaran*), program, funds	*"Where is the funding for the free nutritious meal coming from? It feels like the budget is being forced while other sectors are cut."*
1	General Political Discourse	government, cabinet, prabowo, image-building, policy	*"This program seems more like a political tool for the new administration rather than a genuine solution for nutrition."*
2	Media Coverage Reactions	kompas, news, media, report, bias	*"Why does the news always frame the budget cuts as 'efficiency'? The media should be more critical of these changes."*
3	Regional Issues (Papua)	papua, education (*pendidikan*), school, needs, remote	*"In Papua, we don't just need free meals. We need better schools and teachers first. The central policy doesn't fit our reality."*

Keyword Analysis

To validate the thematic distinctions, we analyzed the Topic Word Scores using c-TF-IDF values as visualized in Figure 2. While general context words such as makan (eat), gratis (free), and prabowo appear across multiple clusters, the analysis reveals distinctive keywords that define the core identity of each topic. For Topic 0, the keywords anggaran (budget) and presiden dominate the discourse. Topic 2 is clearly identified by media-specific terms like kompascom, while Topic 3 is semantically unique, defined by the dominance of Papua, pendidikan (education), and sekolah (school). These lexical distinctions confirm that public negative sentiment is not a monolith, but rather a directed sentiment focused on specific concerns regarding fiscal policy, media framing, and regional inequities.

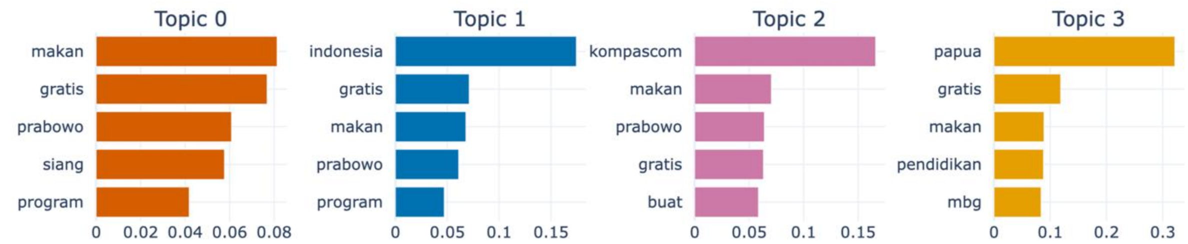

Figure 2. Topic Word Scores

To understand the semantic relationships among these concerns, we visualized the intertopic distances in Figure 3. The spatial arrangement of these clusters provides critical insights into the relationship between different issues.

Interpretation of Cluster Proximity

The close spatial proximity between Topic 0 (Budgetary Concerns) and Topic 1 (General Political Discourse) suggests that public anxiety regarding the program's cost is inextricably linked to broader political skepticism. The fiscal burden of the program is not viewed in isolation but is interpreted through the lens of political trust and governance efficiency.

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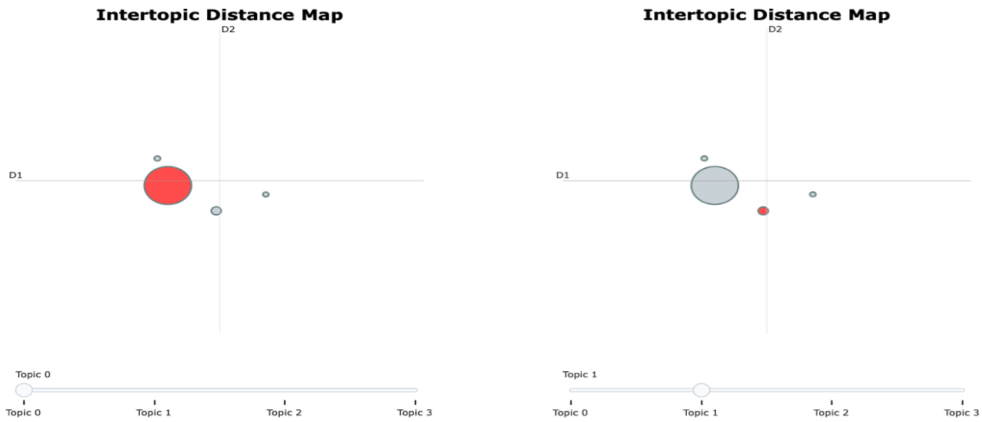

Figure 3. Intertopic Distance Map of Negative Sentiment. The size of bubbles represents cluster volume, while the distance indicates semantic similarity

To further validate this structural relationship, we performed hierarchical clustering as shown in Figure 4. The dendrogram confirms that Topics 0 and 1 merge early, forming a thematic "super-cluster" of political-fiscal anxiety.

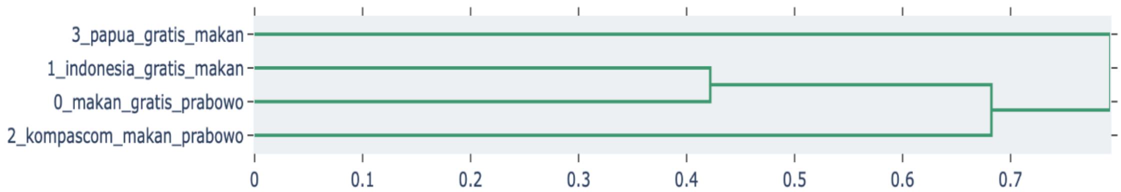

Figure 4. Dendogram

Qualitative Analysis of Distinct Clusters

Conversely, Topic 3 (Regional Issues - Papua) appears as a distinct outlier, spatially isolated from the core political cluster (see Figure 4). This indicates that the discourse in remote regions is driven by unique, localized needs—specifically education and logistics—rather than the central political narrative.

Regarding Topic 2 (Media Reactions), the negative sentiment is characterized by high polarization. Qualitative inspection reveals that this cluster does not reflect hostility toward the media outlets (e.g., Kompas) themselves, but rather demonstrates how specific news reports serve as triggers for political contention. Users frequently utilized the comment sections of these media reports to express dissatisfaction with policy adjustments (e.g., budget cuts), effectively turning media coverage into a proxy for political venting (see Figure 5).

Figure 5. Detailed view of Topic 2 (Media) and Topic 3 (Regional/Papua) illustrating their semantic distinctiveness from the core clusters

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DISCUSSION

The current research deployed a mixed-methods NLP pipeline to evaluate public discourse surrounding the "Free Nutritious Meal" (MBG) program. While the overall sentiment was predominantly negative—aligning with Sianturi's findings of a "messy implementation" (4) —this study argues that treating negative sentiment as a monolith is insufficient for policy evaluation. Instead, the findings necessitate a dichotomy between 'Political Noise' and 'Constructive Feedback'. Policymakers must distinguish between the partisan polarization found in Topic 1 (General Politics) and Topic 2 (Media), which often serves as a proxy for political venting (16,18), and the legitimate, actionable diagnostic signals embedded in Topic 0 (Budget) and Topic 3 (Regional Issues). It is the latter category that offers the critical roadmap for policy improvement.

The Fiscal-Nutrition Nexus: Why Budget Skepticism Threatens Sustainability The dominance of Topic 0 (Budgetary Concerns) represents a form of constructive feedback that goes beyond mere fiscal conservatism. In the context of a nutrition policy, public anxiety regarding the budget is inextricably linked to the program's sustainability and quality assurance. As noted by Thawley et al., the initial volatility of the IDR 400 trillion cost estimate triggered genuine fears regarding national fiscal stability (1). However, this study posits a deeper implication: if the public perceives the budget as mismanaged or prone to corruption, trust in the program's ability to deliver consistent, high-quality nutritious meals diminishes. This skepticism poses a direct threat to participation rates. As Soma et al. found, parents are already skeptical about hygiene and the potential for corruption in school meal programs (5). Without transparent fiscal governance, the MBG program risks being perceived not as a health intervention, but as a liability. Therefore, addressing budgetary concerns is not just an economic imperative but a nutritional one; financial transparency is the prerequisite for public confidence in the "Food is Medicine" approach (3).

Health Equity and the Failure of 'One-Size-Fits-All' in Papua The isolation of Topic 3 (Regional Issues - Papua) is perhaps the most novel and critical finding of this study. It highlights a significant failure in context-sensitive policy making. The discourse in Papua, which prioritizes "education" and "schooling" over food handouts, suggests that a uniform, top-down nutrition policy is ill-suited for decentralized regions with distinct structural deficits. This mirrors the findings of Russell et al. in Australian Indigenous communities, where policies prioritizing community-led self-determination were favored over paternalistic interventions (10). In Papua, the MBG program confronts a "hierarchy of needs" problem: nutritional interventions may fail to gain traction if foundational determinants of health—such as education infrastructure and logistics—are not addressed first. This aligns with Chepo et al.'s analysis in the UK, where geographic inequities in service delivery fueled significant public resentment and undermined health equity goals (12). Thus, for Eastern Indonesia, the MBG program must evolve from a centralized distribution model to a localized empowerment model, potentially leveraging local resources like marine protein (19) or Moringa oleifera (20) to align nutritional goals with regional economic realities.

Navigating Political Noise for Effective Governance Conversely, Topic 1 and Topic 2 largely represent 'Political Noise' driven by media framing and partisan allegiances. The proximity of these clusters in our analysis confirms that for many users, the MBG program is a proxy for broader political contestation, similar to the "toxic discourse" observed by Bell and Westoby (18). While this sentiment drives high engagement, it offers limited diagnostic value for technical policy improvement. Policymakers should therefore filter out this noise and focus resources on the substantive issues raised in the Budget and Regional clusters.

Limitations and Demographic Bias It is crucial to acknowledge that these findings are derived exclusively from the X (formerly Twitter) platform. In Indonesia, X users tend to be more urban, educated, and middle-class compared to the general population (17). Consequently, the dominant concerns captured in this study—such as high-level budgetary scrutiny and political governance—likely reflect the priorities of the middle class. The voices of the most vulnerable rural beneficiaries, who may prioritize immediate food access over fiscal deficits, are likely underrepresented in this dataset. Future research should employ direct field surveys to capture these silent voices and ensure a more holistic understanding of the program's reception.

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Conclusion and Implications The gap between the clinical urgency of stunting reduction (2) and the low public acceptance of the MBG program (4) signals a need for a strategic pivot. To secure the program's future, the government must: 1. treat budget transparency as a core component of nutritional quality assurance to rebuild trust (Topic 0); 2. abandon uniform implementation in favor of context-sensitive strategies that address regional disparities, particularly in Papua (Topic 3); and 3. utilize social listening not just to gauge popularity, but to identify and resolve specific implementation bottlenecks (16,17).

CONCLUSION

This study deployed an NLP pipeline to assess public discourse on the MBG program, revealing that negative sentiment is not monolithic but comprises distinct diagnostic signals regarding fiscal anxiety and regional disconnection. The findings confirm that public resistance is driven primarily by equivocal communication regarding funding and a lack of context-sensitivity in remote regions.

To address these challenges, this study offers concrete policy recommendations. First, to mitigate fiscal skepticism (Topic 0), the government must prioritize budgetary transparency and clearly communicate the staged financing plan to rebuild public trust. Second, addressing the center-periphery disconnect requires more than just tailored messaging; it necessitates establishing a formal regional feedback mechanism. This mechanism is essential to detect and resolve local anomalies—such as the specific demand for educational infrastructure over food observed in the Papua cluster (Topic 3)—thereby preventing policy failure in decentralized regions. Finally, future research should extend this methodology longitudinally to monitor how these public concerns evolve over time, ensuring that the program adapts to the dynamic needs of the Indonesian population.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest

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